AGENT-BASED SIMULATION FOR EVALUATING THE IMPACTS OF DESIGN ON NURSES' SPATIOTEMPORAL EXPERIENCE

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AGENT-BASED SIMULATION FOR EVALUATING THE IMPACTS OF DESIGN ON NURSES' SPATIOTEMPORAL EXPERIENCE

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To Dita & Iraj

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LIST OF SYMBOLS AND ABBREVIATIONS

CCE	Care provider- to – Care provider Encounter
ICU	Intensive Care Unit
CICU	Cardiac Intensive Care Unit
NS	Nurse Station
DNS	Decentralized Nurse Station
IV	Intravenous Therapy
ECHO	Echocardiogram
EKG	Electrocardiogram
ECMO	Extracorporeal Membrane Oxygenation
CCEt	Care provider-to-care provider encounter time
CCEn	Care provider-to-care provider encounter number

SUMMARY

Studying dynamics of care providers' spatial experience based on their space occupancy and activity patterns allows us to better understand the impacts of design on care providers' outcomes. During the early stages of design, computer simulation models can be used to evaluate design options for optimizing care providers' spatiotemporal experience. Current simulation platforms offer advanced capabilities for modeling workflows and activities but have limitations in spatial analytics.

This study focuses on developing an agent-based simulation model for evaluating the spatiotemporal experience of care providers based on layout attributes. The proposed model integrates spatial analytic methods into a simulation platform in order to investigate impacts of the layout on care providers' encounters as an example of spatiotemporal events. Observational data collected from a pediatric cardiac intensive care unit is used to inform the simulation. The model records the care provider agents' encounters measures defined by unobstructed lines of sight between agents within a defined field of view and distance threshold, including agents' encounter durations (CCEt) and encounter counts (CCEn).

Bivariate analyses of the simulation encounter output and layout attributes show that changes in "compactness" and "betweenness" levels of bedside nurse agents' locations are associated with changes in CCEt and CCEn measures. These associations are in alignment with records of interactions collected through on-site observations of similar locations and confirm assumptions of the present study. Enhancing simulation platforms through the integration of spatial analysis methods can provide further insights into understanding the impacts of design on building occupants' spatiotemporal experience.

CHAPTER 1. INTRODUCTION

This chapter presents the research background on the importance of studying care providers' spatiotemporal experience in healthcare settings. It also reviews existing research studies on applications of simulation in designing healthcare environments and simulating human spatial behavior to understand exiting knowledge and technological gaps. The chapter concludes by describing the research goals and objectives of this study.

1.1 Background

Healthcare environments are complex and diverse settings. The complexity of healthcare environments comes from process dynamics (various usage patterns, functions and user groups), interface dynamics between individuals (care provider-care provider dynamics and care provider-patient dynamics), and organizational dynamics (changing working shifts and composition of professionals) (Pachilova, Sailer, & King, 2017). In such complex systems, care providers' movements are initiated by tasks, care processes, individual activities and are further determined by the spatial layout of their work environment. Space moderates the way care providers perform their daily tasks, and changes care providers' movement patterns. Movement of individuals in space creates a mechanism that exposes individuals to ongoing activities and different visual clues and creates awareness of other people that are not directly visible from their workstations (Peponis et al., 2007). As care providers' movement patterns change, their spatial experience changes as well. Constant movements of care providers create a dynamic environment where care providers experience continuously changing spatial qualities as they perform different tasks, walk or occupy different spaces.

This study emphasizes the importance of understanding the temporal aspects of care providers' spatial experience in healthcare settings, considering the dynamic nature of their activities. Care providers frequently switch between different tasks and locations during a working shift and, therefore, are exposed to variable environments. Although nurses spend most of their time at patient bedsides or assigned nursing stations for direct care activities and electronic charting, they spend a significant amount of time at other locations for medication, nourishment, and supply delivery or taking breaks. A time and motion study of 767 nurses in 36 medical-surgical units showed that nurses spent 38.6% of their time at nurse stations, 30.8% at patient rooms, 23.75% other locations on the units and 6.9% off the unit (Hendrich, Chow, Skierczynski, & Lu, 2008). Another observational study of nurses in 2 medical-surgical units found reported that nurses spend 56% of their time working at their assigned station, 20% on direct patient care activities, 13% on medication delivery, 4% on supply delivery, 3.5% on nourishment delivery and 3% on breaks (Nanda, Pati, & Nejati, 2015). Considering these occupancy patterns, it is important to understand care providers' spatial experience not only at nurse stations and patient bedsides, where they spent most their time but also at other locations where they frequently visit and while traveling between these locations. Evidence-based design studies show how spatial metrics predict the correlation between spatial organization and care providers' behaviors, activities, movement, performance, as well as patient care and safety (Cai & Zimring, 2012; Heo, Choudhary, Bafna, Hendrich, & Chow, 2009; Lu, Ossmann, Leaf, & Factor, 2014; Lu & Zimring, 2012; Seo, Choi, & Zimring, 2011).

Nurses spend a considerable amount of time walking between patient rooms or other spaces while switching between different tasks. According to a study on staff behavior in a nursing home, walking was the second most frequently observed behavior (28.5%) after patient care activities (Burgio, Engel, Hawkins, McCormick, & Scheve, 1990). Another study on nurses in medical-surgical units showed that walking was the most frequently observed activity constituting 20.1% of all observed activities and among the five most time-consuming activities by 8.1% of total hours after patient care activities, communications, personal time and electronic (Cornell et al., 2010). Existing studies report that nurses walk between 2.1 to 6 miles during a working shift which can take a significant percentage of their time (Hendrich et al., 2008; Nanda et al., 2015; Pati, Harvey Jr, & Thurston, 2012; Welton, Decker, Adam, & Zone-Smith, 2006).

Care providers' movements and workflow have been studied from both negative and positive perspectives for possible impacts on nurses' health, maintaining physical activity, fatigue, job satisfaction, organizational productivity and time spent with patients. However, impacts of the care providers' movements, occupancy patterns, and walking behaviors on their spatial experience is yet to be explored. We can look at the optimum walking behavior from different points of view. If we minimize the care providers walking distances by co-locating the team members in central locations, we minimize the time they spend walking. However, this approach will isolate them and minimizes opportunities for interactions and consultations with other professionals and care providers. From a different point of view, walking long distances can be considered a type of "functional inconvenience", which might create more opportunities for chance encounters with other team members (Becker, 2007). Higher rates of movement might change qualitative aspects of care providers' work by exposing them to information-rich spatial events. Each movement path offers unique spatial experiences when traveled and embodies certain spatial affordances.

Various spatial analysis methods have been used to describe the spatial experience of care providers in healthcare settings. Many of these techniques and representations come from space syntax theory. Space syntax research investigates the relation between spatial layouts and social/behavioral phenomena (ex. movement patterns, interaction, communications, wayfinding, etc.), by describing a continuous space as a set of discrete units which can be assigned to individual people, groups or activities (Bafna, 2003; Hillier & Hanson, 1989). Based on this definition, basic space syntax measures such as visibility, integration, step depth, and connectivity describe the relation of each spatial unit/member relative to other units. Since these spatial units are fixed (predetermined), the social or behavioral phenomena associated with them are fixed as well.

In current space syntax studies, spatial metrics are calculated based on relative locations of specific points in the space, explaining single episodes of behavior and do not capture the dynamic, time-dependent nature of occupancy patterns and movements within the space. Movement patterns and space occupancy have a stochastic nature. If we overlook the stochasticity of space occupancy, any predictions about the impact of the spatial environment on behavior might have some degree of overgeneralization.

In healthcare settings, care providers are usually mobile to get their tasks done. Therefore, the temporal aspect of such spatial metrics can be determining in creating better patient and care provider outcomes. Studying the dynamic nature of care providers' spatial experience based on space occupancy patterns in healthcare settings allows us to put forward more realistic predictions about the impacts of different design alternatives on patients and care providers' outcomes. Despite the importance of understanding the temporality of care providers' spatial experience, limited research has been done on understanding the spatiotemporal experience of care providers in healthcare environments. A recent study has suggested using “isovist-minute”, defined as the time a patient is within the care providers’ field of view, to keep track of dynamic visual access to patients based on a hospital real occupancy data captured through surveillance cameras (Gomez, 2017). Another recent study integrated climate-based daylight simulation and discrete event simulation and measured the duration of exposure to useful daylight levels for care providers based on space occupancy patterns to understand the impact of design on health and wellness outcomes (Hadi & Pewzer, 2018).

Further studies are necessary in order to understand the impacts of care providers’ spatiotemporal experiences in healthcare settings. For this reason, the current study focuses on understanding the occurrence of face-to-face encounters among them, as an example of spatiotemporal events. In the definition of this research study, “care provider-to-care provider encounter episodes” explain episodes when care providers have visual access and are close enough to each other while performing different tasks or walking. The next section explains the significance of care providers’ encounters in healthcare environments.

1.2 Care Provider-to-Care Provider Encounters (CCE)

Care provider-to-care provider encounters help increase awareness about peers’ situation and facilitates interactions among them. Increased awareness and interactions among care providers reduce communication failures which are associated with negative care provider’s and patients outcomes such as increased resource utilization, care provider dissatisfaction, turnovers, patient length of stay and patient safety (Gordon, Deland, & Kelly, 2015; Pronovost et al., 2003; Vertino, 2014). The role of unplanned encounters has been studied in the field of organizational psychology and a variety of workplace environments but remains under-researched in healthcare settings. Recent workplace research suggests that designing work environments that create collisions (unplanned encounters) between workers increases knowledge transfer and improves workers' performance (Waber, Magnolfi, & Lindsay, 2014). Like other work environments, chance encounters in corridors and common areas of healthcare settings can increase environmental awareness and trigger interactions among care providers. Although chance encounters cannot be planned or determined, we can influence the likelihood of their occurrence indirectly through the design of healthcare environments.

Encounters create opportunities for workplace awareness. Workplace awareness involves knowing about ongoing activities, peers' locations, events, and actions in the surrounding environments without using focused attention, which benefits work processes and learning (Gutwin & Greenberg, 2002). Workplace awareness is beneficial in dynamic environments with high cognitive demands, sense of urgency, and time pressure where there is a need for sharing information, rapid feedback, and task transparency to support coordination (Heerwagen, Kampschroer, Powell, & Loftness, 2004). Healthcare settings are an example of such workplace environments where environmental awareness matters. Visual and aural accessibility and proximity facilitates workplace awareness (Gutwin & Greenberg, 2002) by allowing workers to understand peers' status and knowing if they need help. A study of ICU nurses found correlations between distance measures and measures of co-awareness among nurses. In this study, nurses assigned to alcoves with lower peer distance had higher interaction ratios, and peer awareness measures were negatively correlated to global peer distance of assigned nurse alcoves (Cai & Zimring, 2012).

Encounters enable brief interactions. Brief interactions concern quick task-related and social interactions, lasting less than one minute, for information exchange, individual learning, spreading knowledge, and strengthening social bonds (Bagnara & Marti, 2001; Reder & Schwab, 1990). Interactions constitute a significant amount of staff time in most professions (Brill & Weidemann, 2001). They can be intentional and pre-determined by organizational relations between staff and their mutual tasks. They can also be unintentional, initiated by unplanned encounters among staff in hallways and common areas. Informal brief interactions are essential for coordination between colleagues and fostering their social bonds. They can be beneficial when tasks involve high levels of uncertainty, time pressure, and rapid information transfer (Heerwagen et al., 2004).

Although there are many benefits in interactions, interruptions caused by increased interactions can be problematic by stopping, delaying, or changing individuals' actions or workflow. Interruptions have less impact on simple tasks and routine processes (Zijlstra, Roe, Leonora, & Krediet, 1999). Care providers' work has both cognitive and social aspects. They need time without distractions to focus on their cognitive tasks, such as medication dispensing. They also need time to interact with their peers, transfer knowledge, externalized their concerns, and coordinate patient care. An ideal environment should minimize possible distraction for highly cognitive tasks but encourage interactions in other situations. Although one can question interaction-promoting environments for possible distractions, it could be argued that non-verbal and behavioral clues can attune the situation by sending signals showing openness to interaction and preventing possible unwanted interruptions. Individuals who work together learn to interpret body language and facial expressions of each other and learn about the sensitivity of their peers' activities. It allows them to time the initiation of interactions and conversations and to assess the situation before initiating an interaction (Becker & Sims, 2001).

Most of the brief interactions in work environments occur through unplanned encounters (Penn, Desyllas, & Vaughan, 1999). An observational study of workplace settings showed the majority of interactions were unplanned (80%), unexpected, and took place as a result of movement patterns, incidental proximity, and perceived availability of passerby for getting involved in conversations (Backhouse & Drew, 1992). This study emphasized the importance of line of sight and proximal availability in creating opportunities for interactions. What individuals can see will encourage or prevent them from interacting and engaging in collaborative participation. Visual access plays an important role in stimulating interactions by reminding people of existence of potential communication partners and the availability of professional help within their institution (T. J. Allen, 2000). The current literature describes how visibility is associated with interactions and movement patterns in organizational and healthcare settings (Cai & Zimring, 2012; Peponis et al., 2007; M. Rashid, Wineman, & Zimring, 2009).

When studying person-to-person relationships in space, distance is one of the most important features. Proximity determines the occurrence of interactions in organizations. Allen's studies found that spontaneous interactions happened in closed proximities under 30 meters and deliberate movements to get engaged in interactions significantly decreased by distance (T. Allen, 1977). Allen studied the frequency of interaction between individuals in research and development laboratories and product development organizations related to the walking distances between desks. Based on the results of his studies, probabilities of communications decreased with distance, and the separation distance influenced the probability of communications within the first 30 meters (T. J. Allen, 2000; T. J. Allen & Fusteld, 1975). Allen’s studies also showed the complexity of movement paths (more corners and more connecting pathways) was associated with decreased interaction levels (T. Allen, 1977). Wineman (2014) studied the impact of proximity on the performance of three different organizations, including a life science institute, a software company, and an automobile manufacturing company. This study found that different metrics of spatial of proximity including mean distance (measure of mean metric distance between an individual’s workstation and all other professional employees’ workstations) and metric choice (extent to which an individual’s workstation is on or near spaces that are on the shortest path when moving from all professionals’ workstations to all others) were predictors of participation in innovative activities and collaboration. It suggested that locations with high metric choice and low mean distance, provide opportunities for chance encounters among individuals (Wineman, Hwang, Kabo, Owen-Smith, & Davis, 2014).

Interactions mostly result from movement patterns that make individuals available for getting involved in conversations. Although access to interaction-promoting areas such as key shared spaces within a setting promotes interactions (T. J. Allen & Fusteld, 1975; Hua, Loftness, Heerwagen, & Powell, 2011), interactions usually happen in main corridors or near workstations (Heerwagen et al., 2004). In fact, spaces designed for informal interactions are rarely used for this purpose (M Rashid, Kampschroer, Wineman, & Zimring, 2004). Existing studies have shown the importance of unplanned corridor interactions among healthcare staff in supporting the timely sharing of clinical information and knowledge transfer for improving patient care and reducing errors.

A study of interaction patterns among medical-surgical nurses pre- and post-move to a new nursing units showed that a significant proportion of nurses' interactions happened while they were walking between rooms (29.47% pre-move and 30.45% post-move) (Hua, Becker, Wurmser, Bliss-Holtz, & Hedges, 2012). An observational study of nurses in specialist inpatient rehabilitation units showed that nurses used corridors as places for interactions, quick catchups, incidental discussions, and interdisciplinary conversations. Nurses explained that corridors allowed them to interact with others while keeping an eye on their patients, to interact with other professional staff who were in their private offices otherwise, and to have informal and "easy" conversations with others (Colley, Zeeman, & Kendall, 2017). An ethnographic study of staff interactions in two day-surgery units highlighted the importance of corridors as one of the "backstage" areas for informal knowledge sharing, contribution to organizational learning, clinical practice and patient safety. The occurrence of knowledge sharing activities at backstage areas of healthcare settings can contribute to the clinical practice by helping care providers identify risks, reduce ambiguities in work processes, deal with changes in context, assist decision makings and support colleagues (Waring & Bishop, 2010). A study of outpatient clinics by Iedema, Long, and Carroll also emphasized the importance of corridor conversations as a space that enabled incidental and informal clinical consults for a timely response. This study videotaped and observed interactions between and among clinical teams in corridors. The findings showed how professional boundaries between doctors, nurses, and other health staff were suspended in corridors and allowed staff to engage more often. This matter has clinical implications for patients' safety because it allows clinicians to address complexities easier through "reflection-in/on-action' (Iedema, Long, & Carroll, 2010).

Although the design of the space creates potential affordances for face-to-face encounters, it does not directly determine the chances of those encounters. It is the concurrency and co-location of activities within the space that initiate interactions, conversations, and information transfers. The co-presence of individuals in corridors, defined as "the number of individuals seen from any point on a circulation path", has been correlated to the occurrence of interactions as well (M Rashid et al., 2004). Social density, defined as "number of individuals within 50-feet", has been associated with higher levels of information exchange and interactions (Szilagyi & Holland, 1980).

For studying possibilities of care provider-to-care provider encounters in a healthcare setting, an understanding of spatial attributes, occurring activities, and timing of those activities, therefore, is required. The probability of two care providers' encounter depends on what the sequence of their activities are, where these activities happen within the space and when these activities happen. These factors bring different levels of variability to the equation of encounters, which have not been yet extensively explored in the field of healthcare design.

1.3 Modeling Care Provider's Spatiotemporal Experiences

Studying the sequential aspects of space occupancy is necessary to understand care providers' spatial experience in different situated tasks and operations. To understand care providers' space occupancy patterns, we need to identify the sequence of their activities and movement patterns. This can occur by studying a live setting, documenting care providers' movement patterns and variations in time and sequence of their activities. However, this documentation also allows us to model the dynamics of their movements and approximate time episodes that they might spend at different locations in as-yet-unbuilt settings to understand the potential impacts of different designs on spatiotemporal experiences.

A simulation model of care providers' activities allows us to study temporal dimensions of their experience as they occupy space. Various predictive models have been used to explain care providers' behavior in healthcare systems, including statistical and simulation models. Statistical models, such as linear models, have limitations in capturing dynamic aspects of healthcare systems, including processes and activities initiated upon occurrence of certain events in emergencies and unplanned procedures (Choudhary, Bafna, Heo, Hendrich, & Chow, 2010). In situations where workflows involve high degrees of variability or circumstantial decision making about the next steps in the process, such as those in healthcare settings, simulation modeling offers better predictive opportunities over statistical modeling. In order to study the spatial experience of care providers in healthcare settings, we need to consider care providers' roles, choices of work strategy, the variability of spatial behaviors and movement patterns, as well as interactions with their environment, peers, and patients. Simulation modeling allows the implementation of different behavioral logics for different care providers based on their roles, schedules, events, and individual choices.

1.3.1 Simulating Healthcare Environments

In order to model spatiotemporal measures such as encounters, we need platforms with embedded capabilities for integrating both human activity and spatial data into system models. Existing Computer-Aided Design and Building Information Modeling technologies have limited capabilities in applying time and activity sequence concepts and integrating dynamic occupant's behavior in building models. Simulation technologies, on the other hand, are very robust in terms of time and process constructs, but not very advanced in embedding spatial analysis.

Simulation models are representation of real-world systems and processes which can serve as virtual labs for testing what-if scenarios. Most of the simulation modeling efforts in planning of healthcare facilities related to the physical environment are either about determining capacity requirements of facility resources such as number of beds and rooms or about examining the relationship between bed/room numbers and performance measures of healthcare systems such as patient waiting times, patient throughput, and resource utilization (Jacobson, Hall, & Swisher, 2006). Such simulation models are usually abstract with no reference to spatial layouts. Only a few studies have focused on assessing different layout options through alternative simulation scenarios. These studies compare the simulation outputs for different layouts in healthcare settings to examine the relation between design of healthcare facilities and defined performance measures (Butler, Karwan, & Sweigart, 1992; Groothuis et al., 2002; Khurma, Bacioiu, & Pasek, 2008; Mahachek & Knabe, 1984; Morgareidge, Jia, & Cai, 2014; Rohleder, Huschka, Egginton, O'Neil, & Woychick, 2010; Sepulveda, Thompson, Baesler, Alvarez, & Cahoon, 1999). However, they do not apply and track any spatial measures related to human behavior in simulation models, other than walking distances.

Different categories of simulation have been used in studying healthcare systems, including discrete event and agent-based modeling. In common practice of using discrete event simulation in designing healthcare systems, the model represents the system as a process and a sequence of activities usually performed by patient entities. In such models, the providers are modeled as passive resources with aggregated behaviors. They move in the environment when their presence in certain places is required for specific processes. Although discrete event simulation models can represent the dynamics and stochasticity of organizational processes, they do not capture the heterogeneous behavior of individual providers, their reactions to their environment, and their interactions with their peers.

Unlike discrete event models, agent-based simulation models have a bottom-up approach where the behavior of individual objects defines how the system behaves. Agent-based models consists of a set of interacting, autonomous agents that interact with a set of objects, their environment, and other agents and can make autonomous decisions. An agent-based simulation model is formed from defining the agent characteristics, environment, and interactions. The environment is the layout within which agents operate. Agents are created through defining agent types (doctors, nurses, patients, equipment), agent profiling (assignment of characteristics to agents), and rule assignment (rules that define interactions between agents and environment) (Friesen & McLeod, 2014).

In order to study the spatial behavior of care providers in healthcare settings, we need to consider different provider's roles, the variability of their spatial behavior, movement patterns, and their interactions with the surrounding environment and other providers. By using an agent-based approach, we can define adaptive behaviors for agents and allow them to have conditional behavior changes based on specific states or spatial clues in their environment. By setting a defined environment, inserting the agents in that environment, and allowing them to behave based on rules assigned to them, an agent-based model can reveal relations between agents and environment and help us measure spatiotemporal effects of different interventions.

1.3.2 Simulating Human Spatial Experience

In most of the current agent-based simulation studies with a focus on simulating human behavior in relation to their environment, simulated behaviors are studied for outcomes such as required resources, disease outbreak rates and building evacuation time (Bithell, 2016; Jacobson et al., 2006; Van Schyndel, Hesham, Wainer, & Malleck, 2016). Such models do not provide measures of spatial experience for agents and are limited to simple measures such as distance traveled from one space to another. By adding extra layers of spatial analysis to current methods, it is possible to glean additional useful spatial information from simulation models and better understand the spatial experience of agents in their environment.

For simulating human behavior in buildings, it is essential to consider the complex nature of interactions between the physical environment and movement patterns. Although existing simulation packages have limited capabilities in overlaying the simulation models with spatial data, it has become more common to add spatial descriptors, especially in agent-based simulation practice, in order to increase spatial reality of simulation models.

Tools such as Netlogo, StarLogo, Agent Analyst (Agent-Based modeling in ArcGIS), RePast agent simulation toolkit, MASON multi-agent simulation kit and GAMA have been used for adding spatial information layers on agent based models (Bithell, 2016). Other Simulation toolkits such as AnyLogic and Simio also include features for coupling spatial data with agent-based simulation models. A few gaming engines such as Unity3d have capabilities for building spatial representations of agent-based modeling.

Simulation of human spatial behavior has been usually limited to simple, well-defined human activities such as pedestrian traffic simulation and fire egress simulation (Yan & Kalay, 2005). In such models, the impact of spatial features on agent behaviors is explored through defining spatial rules which determines agent next states or steps. Accordingly, the output measures related to agents' spatial experience are byproducts of the simulation run, usually confined to measure the time and distance traveled by agents.

Several simulation studies in computational epidemiology have looked at small-scales settings and explored the spatial behavior of agents in interaction with their environment and physical obstacles. An agent-based simulation model of disease outbreak in a homeless shelter used a grid environment with beds and compartments in StarLogo to study probabilities of infections and percentages of infected agents based on encounters of healthy and infected agents (Patlolla, Gunupudi, Mikler, & Jacob, 2004). A recent study gathered activity data in a small school to explore the interaction between students' socio-spatial behaviors and transmission of diseases based on students' spatial proximity and contact time using agent-based modeling in Netlogo (Bithell, 2016). This study used spatial grids to set obstacles (walls and furniture) for agent movements and identified the locations at which infections took place, recording the total number of infected agents.

Simulations of pedestrian movement and crowd modeling have been used in planning and design of urban spaces and buildings to evaluate the functionality of physical systems in emergency conditions. A multi-method simulation study has investigated the correctness of wayfinding decisions of airport passengers in the Unity 3D environment (a game engine tool) where agents are able to see, perceive, and interpret signs. When an agent is close enough to a sign, then a visibility check is performed using multiple ray-casts. If agents interpret the sign correctly, then the correct next steps will be assigned to them (Becker-Asano, Ruzzoli, Hölscher, & Nebel, 2014). Another study uses multiple-agent systems in integration with space syntax methodologies to simulate pedestrian movement patterns in a more realistic way using Netlogo and Depthmap. After running visibility graph analysis, the visual integration map was imported into Netlogo so that agents could adjust their movements according to the visual integration of adjacent grid cells (Hu, Luo, Chen, Bian, & Tong, 2017). A Stanford study has developed a methodology using SAFEgrass which facilitates agents' navigation in space through implementation of a 2D grid network and computing visibility characteristics of each cell on the grid and as an output shows density patterns of different exiting strategies (Chu, Parigi, Law, & Latombe, 2014). Although studies like these present new techniques for integrating spatial information in agents' decision-making logic, they do not suggest measures for tracking agents' spatial experience and have been used only for simulating simple activities. They take in only simple geometries as the simulation environment and require custom scripting for complex processes.

There have also been efforts in the field of architecture and planning for developing computational methodologies to address the shortcoming of architectural tools in simulating the dynamic character of activities in space and studying spatial measures. Simmone and Schaumann use an event-based computational framework for simulating human behavior in the built environment. This approach places the decision-making abilities in events, compared to agent-based models that embed the decision-making logic in agents. (Schaumann, Morad, et al., 2016). This method encodes the information related to each part of events in a separate database using custom scripting in C# language and connects them to the Unity 3D, which simulates the events and dynamic social and environmental conditions. The movements of actors in the space are based on the defined events and spatial elements, as well as their own narratives and behavior of other actors (Sopher, Schaumann, & Kalay, 2017). This framework was used to explore the impact of medication room location and unplanned interactions (social interactions at close distances) on medication distribution processes (Schaumann, Pilosof, Date, & Kalay, 2016). This methodology presents an innovative framework for measuring spatial events such as the possibility of interactions based on physical proximity. However, it seems to be limited in tracking spatial experience of individual agents (since all the spatial information are stored in room entities rather than agents), integrating line-of-sight constructs (does not include ray-tracing features) and modeling complicated systems (uses custom scripting for simulation logics).

Other efforts for simulation human spatial behavior in the field of architecture include agent-based modeling add-ons for Grasshopper/Rhino, such as Quelea, PedSim, and NURSERY, which allow modeling human spatial behavior through defining primary movement paths or avoiding obstacles but have limited capabilities in modeling complicated processes and systems.

1.4 Research Goal

In order to design healthcare environments that enhance care providers' performance and patient outcomes, it is essential to develop methodologies to assess care providers' spatiotemporal experience before the setting is designed and occupied. Figure 1 shows the existing gap in current methods**Error! Reference source not found.** Current s imulation platforms offer advanced capabilities for modeling complex activities and processes to simulate care provider workflows in healthcare environments. However, they have limitations in spatial analytics for evaluating occupants' spatial experience in such environments. Architecture and design platforms have advanced spatial analysis but are limited in terms of process and system modeling.

The main goal of this research study is to develop a model for measuring the occurrence of spatiotemporal events using stochastic activity data by adding spatial analytics to current simulation platforms. Spatiotemporal events are dynamic events that concern both spatial and time aspects. Measuring spatiotemporal events requires consideration of spatial features in addition to their time dimensions, such as their duration and frequency. By developing such methodologies, we will be able to evaluate the impact of building design on occupants' spatiotemporal experience and compare multiple design options for their performance against certain spatiotemporal events during early stages of design.

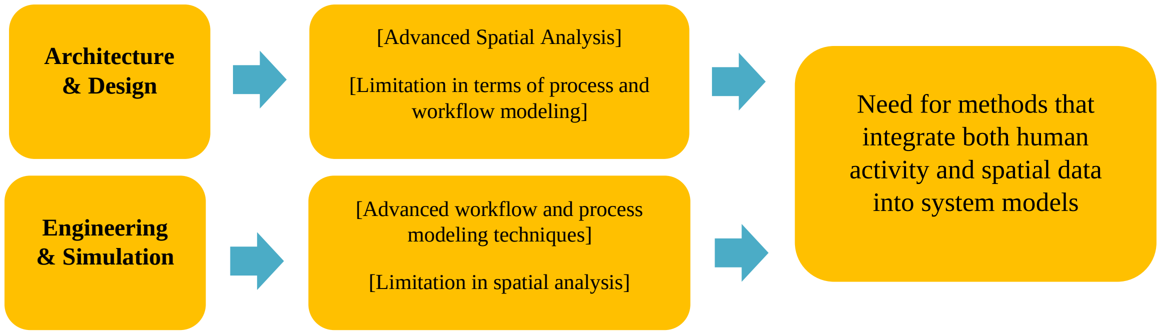


Figure 1 - The knowledge gap

The focus is methodological: developing a simulation model, applying spatial logics to agents, and developing metrics to measure certain spatiotemporal events in the simulation platform. For this purpose, occupancy patterns generated by structured and unstructured activities in a setting and their variability in time and sequence are identified and used to develop the simulation model. As the study site, this research uses care providers' activities and workflow data in a pediatric cardiac intensive care unit (CICU). Observational data on care providers' behavior is collected for testing and validating the model. This research study addresses the following questions:

- How do care providers spend their time in different activities and locations within the unit?
- How can we model the ongoing structured and unstructured activities of individual care providers to simulate the system as a whole?
- What aspects of current simulation techniques need to be further developed for measuring spatiotemporal events?
- Can simulation modeling help in understanding the impacts of design on care providers' spatiotemporal experience?

This study hypothesizes that we can evaluate the impacts of a layout on care providers' spatiotemporal experience during design development stages using simulation modeling, instead of assessing through empirical testing in post-occupancy evaluations. In other words, simulation modeling will perform alike empirical testing in evaluating a layout for the likelihoods of creating defined spatiotemporal events. Simulation modeling during early design stages has various advantages compared to empirical testing through post-occupancy evaluations. It allows us to rapidly test multiple design options and compare them in their potentials for creating the best spatiotemporal experience for care providers before building the healthcare unit.

To test this hypothesis, the simulation model in this study is be used to explore associations between layout features of a layout and care providers' encounters (as an example of spatiotemporal events) by simulating space occupancy. The goal is to determine if the simulation outputs on the layout performance, measured by care providers' encounters, will be comparable to the care providers' interaction data for the same layout.

1.4.1 Impacts of the Layout Features on Encounters and Interactions

A combination of syntactic aspects of a layout and occupancy patterns within the layout influences the occurrence of care providers' encounters and, therefore, face-to-face interactions among them in healthcare settings. In order to understand this relationship, it is important to recognize different types of interactions and the mechanism through which they happen.

Interactions can be planned or unplanned. Planned interactions usually pursue a clear goal of getting help for patient care or consulting an important issue with peers. In the case of planned interactions, the critical nature of patients requires care providers to seek the help they need, no matter how the space has been laid out. Although the design of the environment can facilitate access to peers in these situations, it cannot change the probabilities of occurrence of these interactions.

Unplanned interactions, on the other hand, happen based on spatial circumstances when co-presence and visual access of care providers within the space (defined as encounters) creates an opportunity for starting a conversation or quick information transfer. The unplanned interactions can happen when care providers are seated at their assigned locations or when they are on-move between different locations.

Nurses are more likely to engage in unplanned interactions in spaces where they have a higher number of individuals around them. A study found the number of individuals within 50 feet, as they called social density, was associated with higher levels of information exchange and interactions (Szilagyi & Holland, 1980). Based on this definition, compact layouts with higher density of patient rooms, centralized and decentralized nurse stations have higher social density and can be associated with higher levels of encounters and, therefore, higher chances of interactions for nurses assigned to them. In layouts with higher social density, care providers have a higher number of visible individuals within their 50-feet diameter and therefore are more likely to interact.

In addition to design, building occupancy and movement patterns can influence the occurrence of unplanned encounters. A study found that higher choice or betweenness levels (extent to which an individual’s workstation is on or near spaces that are on the shortest path when moving from all professionals' workstations to all others) were associated with more interactions (Wineman et al., 2014).

Based on these studies, two layout features are associated with higher likelihood of interactions. The first layout feature is "compactness". The compactness level for a specific area in a layout can be defined by the level of social density or the number of individuals within 50 feet assigned in that area. The second layout feature is "betweenness". The betweenness level for a specific area in a layout can be defined by the number of shortest paths between every two other locations that pass through that area. The higher the number of paths, the higher is the betweenness level for that area.

The diagram presented in Figure 2 shows how the design of a layout can be associated with higher probabilities of interactions through changing the spatiotemporal experience of care providers. In spaces with higher levels of compactness, individuals would have more neighbors around them. Therefore, they get long episodes of visual exposure to a higher number of neighbors around them, which means longer episodes of encounter. Long encounter episodes can be associated with more seated interactions. In spaces with higher levels of betweenness, individuals would have a higher number of people passing through their area. Therefore, they get more frequent episodes of short visual exposure to a higher number of individuals, which means more frequent encounter events. Recurrent episodes of encounter can be associated with more on-move interactions. In summary, areas with higher levels of both compactness and betweenness would be associated with more opportunities for unplanned interactions.

The study uses simulation modeling to explore the association between layout features such as compactness and betweenness, with care providers' spatiotemporal experience, such as encounters. The goal is to test if the occurrence of encounters in relation to the layout as the output of the simulation model will be comparable to the occurrence of unplanned interactions in the real setting. If we can confirm this relationship, then we can confirm the assumptions of this study on advantages of using simulation modeling for evaluating the performance of different design options in their potentials for impacting care providers' spatiotemporal experience.

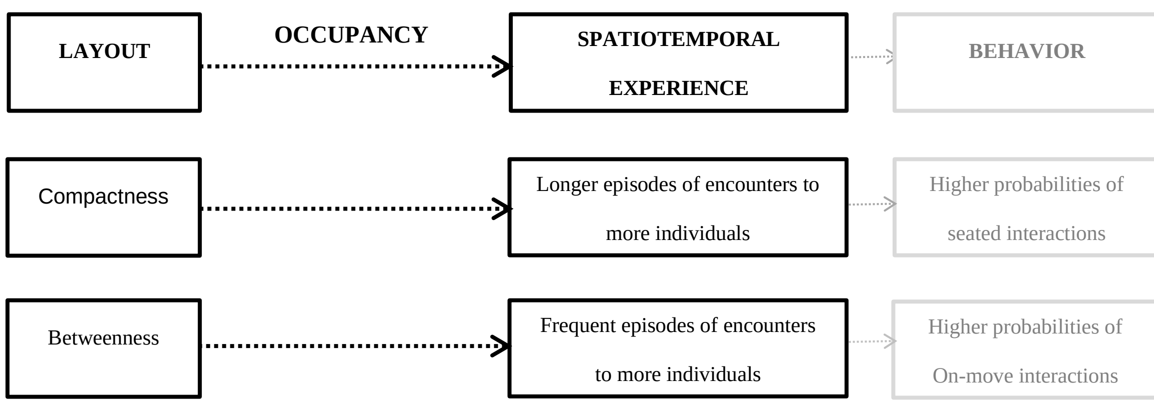


Figure 2 - Conceptual framework of study assumptions. The arrows show hypothesized associations. The black outlines highlight the scope of the study.

1.5 Study Methods

This study uses a pediatric cardiac intensive care unit (CICU) as the study site. The selected unit represents an example of healthcare environments where care providers' activities involve high levels of variability and complexity. In such a dynamic environment, understanding the spatiotemporal experience of care providers in relation to their spatial occupancy and activities becomes crucial. The CICU layout has three pods, each presenting different design features, which allows for comparison of care providers spatiotemporal experience based on their assigned locations in each pod.

In order to model the spatial occupancy of care providers, we need to understand patterns, locations, and timing of their activities. This study uses observation and shadowing to collect data on care providers' activities and interactions. It focuses on understanding nurses' spatiotemporal experience as the primary care provider category in the CICU. Although nurses are the focus of this study, activity data on other care provider categories will be collected to understand their interactions with nurses. In addition to care provider activity data, this study uses the historical patient data to understand care providers' activities concerning different patient categories and profiles.

The collected nurses' activity data is then analyzed to understand how they occupy space for different activities, how often they visit various locations, and what their movement strategies are for performing different activities. The results of this analysis have been used to model individual nurses' activities and movements within the unit. This study also collects information about nurses' interactions, including categories of interactions, location of interactions, and dynamics of interactions with different groups of care providers. The collected data on nurses' interactions is used to model the nurses' planned interactions with other care providers. It also has been used to test the assumptions of the study about the application of spatial occupancy modeling in predicting a layout performance for the occurrence of unplanned interactions.

This study uses simulation to model nurses' activities to study their spatiotemporal experience using Anylogic simulation software. Simulation modeling has been selected as the modeling technique for several reasons, including capturing the high degree of variability in nurses' stochastic activities and modeling event-based and circumstantial activities in the intensive care unit environments. This study uses agent-based modeling to model unique behavioral logics of individual nurses and their interactions with other care providers and their surrounding environment. Two distinct methods have been used to simulate nurses' activities. Nurses' structured activities have been model by process mapping of sequential activity steps. Nurses' unstructured activities have been modeled by Markov Chains process modeling methods using stochastic matrices for determining probabilities of occurrences of defined activities at defined locations. Spatial analysis methods are developed and integrated into the simulation platform to evaluate nurses' spatiotemporal experience by measuring their encounters with other care providers based on their assigned locations. The simulation model is then validated by comparing the simulation activity logs with the observed activity data.

Based on the outputs of the simulation model, the encounters of agents representing nurses have been compared across different locations in the layout (between three pods) with the occurrence of observed unplanned interactions at the same areas to test the assumptions of this study. The assumption of this study is that the simulation modeling will perform similar to the experimental testing in comparing the nurses' encounters in three different pods of the CICU. The results of this analysis are reported and discussed at the end, along with future research directions and contributions of the current study.

CHAPTER 2. DATA COLLECTION

This chapter presents an introduction to the study site: the built environment, care provider categories, and their responsibilities. It also includes a description of tools and methods used for data collection in this study. This chapter also contains a brief summary of observation processes and records.

2.1 Description of the Study Site

For the purpose of this study, the ideal site would have the minimum patient movements to allow focusing on care providers' patterns. The Sibley Heart Center at Children's Healthcare of Atlanta provides such a setting at Egleston hospital. This hospital includes three children's intensive care units: Cardiac Intensive Care Unit (CICU), Neonatal Intensive Care Unit (NICU) and Pediatric Intensive Care Unit (PACU). The CICU (cardiac intensive care unit) is selected for this study, which is a combination of an open ward and private rooms. It has an L-shape layout with three pods and 27 patient beds (10 private rooms and 17 beds in open-bay layout).

Figure 3 shows the layout of the CICU, which highlights the key areas. The three pods are notably different in overall configurations and room features. Pod1 and pod2 have a semi-racetrack configuration, whereas pod3 is more like a single-corridor layout. Unlike pod3, Pod1 and pod2 have centralized nurse stations. Most rooms in pod1 and pod2 are open, unlike pod3, where most rooms are private. The three pods are connected through solid double doors, which are usually kept open. The main entrance area separates pod2, and 3. Each of the three pods has an assigned medication station, a supply closet, a clean utility, a soiled utility room, and a tube system and functions almost independently.

Figure 3 – Cardiac Intensive Care Unit at Egleston Hospital

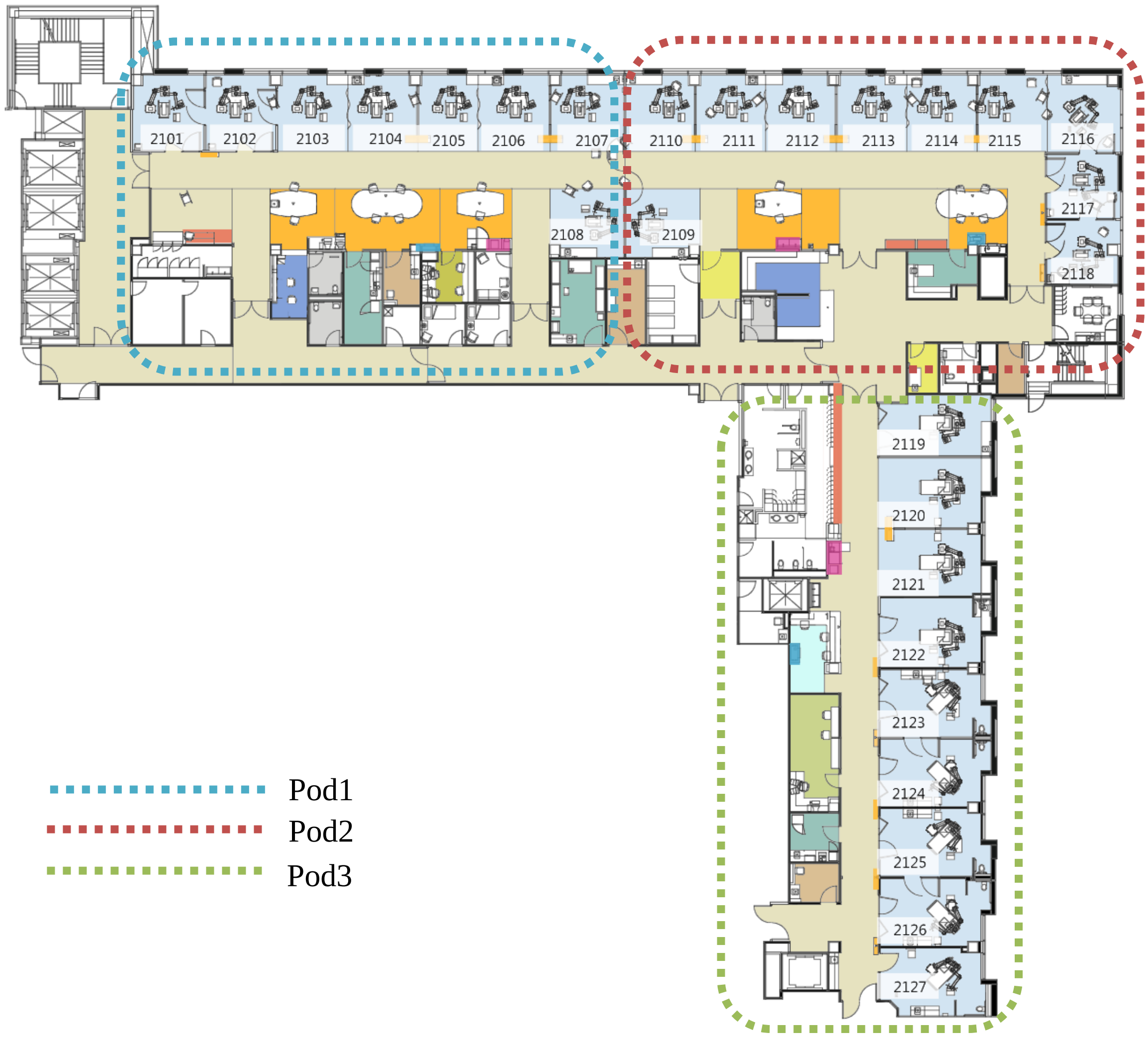


Figure 4 – Map of room and pod numbers

At first sight, pod1 and pod3 look very similar in their design attributes. They are both off-centered compared to pod2 (lower betweenness), they have lower room density compared to pod2 (lower compactness), and they both have key attractor locations (workroom and secondary entrances in pod1; break room and step-down unit entrance in pod3). With a closer look, several differences in the design features of these two pods can be observed. The most notable difference is the location of centralized nurse stations in pod1, where care team members usually spent their idle times. The centralized nurse stations in pod1 also bring bedside nurse agent traffics from other pods to visit the care team members. The other design difference between pod1 and pod3 is their levels of connectedness to the central area in pod2. Pod1 is directly connected to pod2, whereas pod3 is connected to pod2 through a buffer space (reception area). This buffer space further offsets pod3 from all other locations within the unit.

2.2 Data Collection

The data collection phase for this study included detailed documentation of activities, clinical processes, and workflows for each care provider participated in the study (bedside nurses, resource nurses, respiratory therapists and care team members) captured through observations, shadowing, and asking occasional questions from staff on-site in order to create process maps for modeling and simulation. Information on non-clinical activities such as unscheduled or personal activities was also captured through observation and shadowing.

The research protocol for this study was submitted to both Georgia Institute of Technology and Children's Healthcare of Atlanta institutional review boards (IRB) and was approved by both institutions (APPENDIX A). The unit nurse manager informed all CICU staff about the study through an email with the description of study and goals.

Before starting observations, the researcher conducted an unstructured observation session in the unit. The purpose of this observation session was to understand the dynamics of clinical processes in the unit and to determine the scope of the study. At this phase, the organizational hierarchy, roles, assigned workspaces, location of different activities, general workloads, patient categories, room assignments, shift changes, and the unit schedule were specified. The researcher also conducted a pilot observation session with a nurse educator who was the most experienced staff in the unit to understand the workflow and processes. The nurse educator explained and verbalized every step of the care routines to the researcher as they were performed.

For observation sessions, the researcher arrived at the unit before starting the working shift to hire potential participants for the study. Participants were selected based on their availability. The participants were briefly informed about the process and goals of the study. The researcher assured them anonymity and informed them that they could stop the observation anytime they decided. After obtaining consent from the participant, the researcher observed the participant for an entire shift (12 hours) until they left the unit. Limited data on each participant was recorded, including their gender, role, and their assigned rooms.

Once an observation session started, the researcher stayed at least 10-feet away from the participants and did not interact with them unless their activities were unclear to the researcher. Following the IRB protocol, the researcher did not follow the participants in the patient rooms. Most patient rooms were open, and the researcher was able to observe activities going on inside the rooms. If the activities were unclear, the researcher would approach the participants where they were idle and confirmed the activity with them. No information on patients was recorded, except for approximate age and their conditions (ex. eats food, is connected to urine/chest pumps, is post-o/pre-op).

In addition to care provider activity data, this study uses the CICU historical patient data to understand care providers' activities concerning different patient categories and profiles. The CICU patients' types, demographics, admissions, discharge rates, and length of stays are identified by reviewing on-year historical data of the 1,034 CICU patients in discharge records from January to December of 2018.

2.3 Observation Sessions

Data was collected between February 8th to May 1st, 2019 and included twenty-two 12-hr day shifts, in addition to two shifts of pilot observations, with a total of 300 hours. Observations occurred between 6:30 am to 7:30 pm during weekdays and weekends. Out of the 22 shadowing sessions, 17 episodes was on observing bedside nurses, two on resources nurses, one on a respiratory therapist, one on a nurse practitioner, and one on an attending physician (Table 1). The observation included nurses assigned to one or two patients. Out of the 17 observation episodes of bedside nurses, 6 of them were on one-patient assignments and 11 on 2-patient assignments. The observation strategy was to make sure that observations cover all rooms in the unit. Out of the 27 patient rooms in three pods, the observation sessions covered 23 rooms. Three rooms were observed in multiple shifts. This study limited the observation sessions only to the morning shifts. It did not include observations of patients on ECMO (Extracorporeal membrane oxygenation), because bedside nurses assigned to these rooms were extremely busy with the patient care process and did not agree to participate in the study.

Table 1 – Observation episodes

Observation	Pod	Role	#Patients assigned	Room Number
1	2	Bedside	1	2109
2	2	Bedside	1	2110
3	NA	Resource2	NA	NA
4	1	Bedside	1	2103
5	2	Bedside	1	2112
6	2	Bedside	2	2112-2113
7	2	Bedside	2	2112-2113
8	3	Bedside	2	2119-2120
9	2	Bedside	1	2112
10	3	Bedside	2	2126-2127
11	NA	Resource	NA	NA
12	3	Bedside	2	2122-2123
13	3	Bedside	2	2124-2125
14	2	Bedside	1	2117
15	2	Bedside	2	2115-2117
16	2	Bedside	2	2116-2114
17	1	Bedside	2	2104-2105
18	1	Bedside	2	2107-2108
19	1	Bedside	2	2101-2102
20	NA	Respiratory Therapist	NA	2106, 2107, 2108, 2109, 2110, 2111, 2112
21	NA	Nurse Practitioner	NA	2101,2102, 2103, 2104, 2106,2112, 2116,2118, 2121, 2122, 2124
22	NA	Attending Physician	NA	2108,2109,2110,2114,2115,2117,2119,2120,2123,2125

2.4 Data Collection Tool

The GIS Collector application was used for data collection in this study. The GIS collector app is usually used for collecting geographical information about outdoor spaces. A workflow was developed to use this app for indoor data collections on the study site. As a result of this development, the researcher was able to collect information on care providers' activity categories, time and locations. In order to capture on-site data using GIS Collector, the layout of the site was imported into the GIS portal with added feature layers for recording data. The collected data on GIS Collector was uploaded on the GIS web portal and became available to download in different formats.

2.4.1 Adding Feature Classes to GIS Collector Application

The first step was to create a new map in ArcMap software and adding a new Geodatabase file to the map to store the related data. The layout of the CICU unit in DWG format was added to the map as a shapefile layer (a layer containing shape data) and was geo-referenced to the related geographical coordinated to recording the location of data points. In order to add location data points to the map, domain properties, data fields, and feature classes were defined in the Geodatabase and were added to the map.

For the purpose of this study, two features classes were defined to record the location of activities. The first feature class, "Activity Data", was defined to collect information on care providers' activities location. The feature type for this feature class was selected as "Points Features" to record the geographical location points where the activities happen. The second feature class, "Activity Path", was defined to collect information on care providers' movement paths. The feature type for this feature class was selected as "Polylines Features", which allowed for drawing movement paths on the map. When creating the feature classes, the same coordinate system as the geo-referenced layout was selected to allow features to be projected accurately on the layout.

The next step was to define data fields for feature classes to record information related to activity points and activity paths. Data fields provide the structure of information and rules for the types of information collected on a feature. Multiple data fields were defined for the “Activity Data” feature layer, including Activity Description (Text), Activity Category (Coded text values), Activity Start Time (Date), and Activity End Time (Date). The Data format allows for assigning time to the collected data in the MM/DD/YYYY, hh:mm:ss format. Multiple data fields were defined for the “Activity Path” feature layer, including Movement Description, Movement Category, Movement Start Time, and Movement End Time (Figure 5).

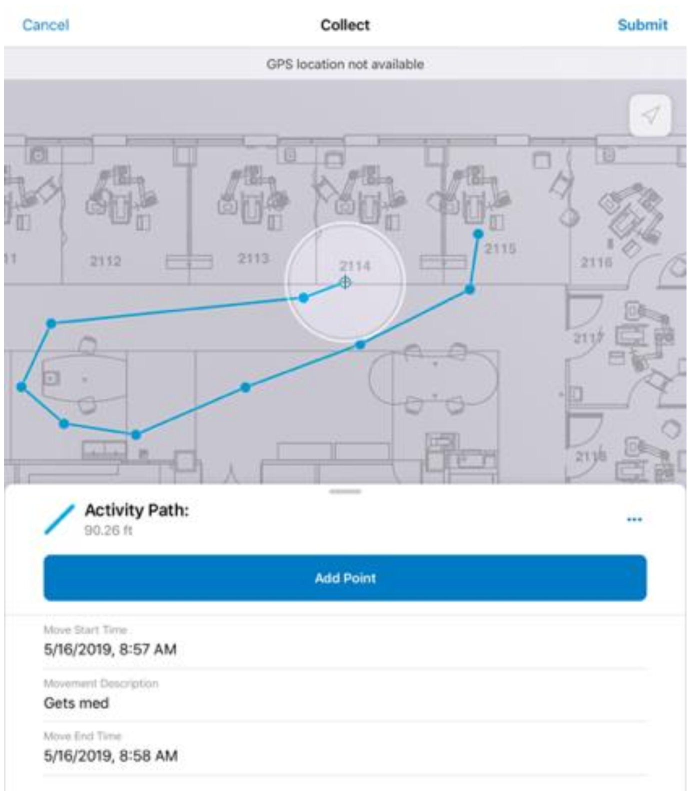


Figure 5- Data fields defined for “Activity Path” Feature Class

2.4.2 Publishing the GIS Map to the GIS Web Portal

The feature classes defined for activity data and activity paths were published to the ArcGIS online server to become available as layers for using on layout map. The layout map, in addition to feature classes, were published to the ArcGIS portal by publishing it as a service. The web map and feature layers can be accessed from the Collector application on a mobile device such as an iPad to collect data. After downloading the web map on a mobile device, we can use feature layers to input and submit data on the web map. The collected data can be downloaded from the web portal in different formats, including CVS, shapefile, and GeoJson. Table 2 shows an example of collected data after downloading from the GIS web portal.

Table 2 – Sample collected data downloaded from ArcGIS online portal

OBJECTID	Activity Start Time	Activity Description	Activity End Time	GlobalID
3218	3/30/19 10:38	Handoff	3/30/19 11:00	f2652965-bf36-459f-99ca-c3d361e1f895
3219	3/30/19 11:01	Participate in nurse rounds	3/30/19 11:01	37856e5c-a8e7-4ca4-b037-4f57c1070b50
3220	3/30/19 11:01	Chart	3/30/19 11:06	50277cde-a05d-427c-a550-7be5e62840ee
3221	3/30/19 11:06	Checks on pt	3/30/19 11:08	bf7f8a53-a9eb-47f2-a5f7-89ea20d9f168
3222	3/30/19 11:09	Change diaper	3/30/19 11:10	1120925a-5d36-49a3-94c6-dc0535ad347d
3223	3/30/19 11:10	Assess pt	3/30/19 11:11	db59dbb4-e5bf-4bf1-bac4-dc8fe04dcd06
3224	3/30/19 11:11	Check pt	3/30/19 11:12	f9fdfd99-5ade-4558-bc2c-d7912fce12d1
3225	3/30/19 11:12	Hands off	3/30/19 11:16	41ddac1c-1565-413d-b936-c69048d8adbc
3226	3/30/19 11:16	Talks to 2121 nurse	3/30/19 11:18	5e1cb480-b64a-403f-88ed-89b1d654f8c9
3227	3/30/19 11:18	Checks on pt	3/30/19 11:21	daf004d7-c478-4b0e-a9fe-60529741de20
3228	3/30/19 11:21	Cleans the room	3/30/19 11:27	3fa587e7-22d3-4220-a74b-3b923904d04a
3229	3/30/19 11:27	Talks to 2121	3/30/19 11:28	ba43476e-ba64-4787-a376-b4f555d2cf02
3230	3/30/19 11:28	Chart	3/30/19 11:29	2fea1f94-777f-4828-bf50-46d60f5519ad
3231	3/30/19 11:29	Cleans the room	3/30/19 11:32	969cef1c-231f-4518-b2ad-b998dd03103e
3232	3/30/19 11:32	Chart	3/30/19 11:40	2c3b3c2a-8db0-410f-9d8a-8962ce238352

2.4.3 *Collecting Observation Data Using GIS Collector*

The shadowing data for each observation session was recorded using a tablet through GIS Collector application. During each observation session, a care provider (bedside nurse, resource nurse, respiratory therapist, attending, or advance practice practitioner) was shadowed for an entire working shift. All the activities and movement paths of that care provider were recorded with time and location data associated with them. In addition, all the interaction between the participant care provider and others was recorded with related information, including the location, time, and the purpose of the interactions, if any. The collected data was then exported to shapefile and CVS formats and was used for visualization in Rhinoceroses software using Grasshopper add-on.

Because of the fast pace of on-site data collection, some data points were missing or misplaced, which were organized and reassigned to the geometries containing the collected data. After visualizing the geometries, the collected data was analyzed to understand activities, movement patterns, and interactions of care providers within the ICU.

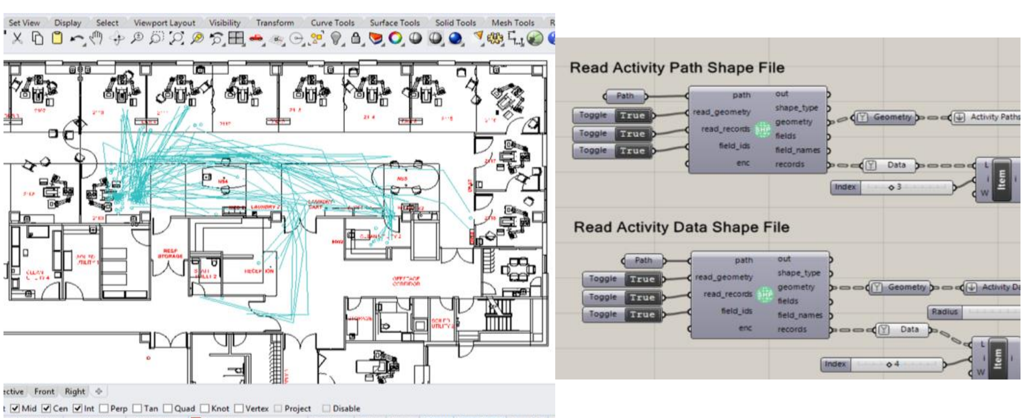


Figure 6 – Importing shapefiles and transferring geometries to Rhinoceroses

2.5 Data Analysis Tool

Using Tableau software, all activity data and paths were visualized and mapped to analyze the collected data. The Figure 7 and Figure 8 represents the shadowing data for 22 observation session including 17 observation episodes from bedside nurses, 2 observation episodes from resource nurses, one observation episode of a respiratory therapist, one observation episode of a nurse practitioner and one observation episode of an attending doctor. This study focuses on understating the activity and occupancy patterns of bedside nurses while considering their relations and interactions with other care providers.

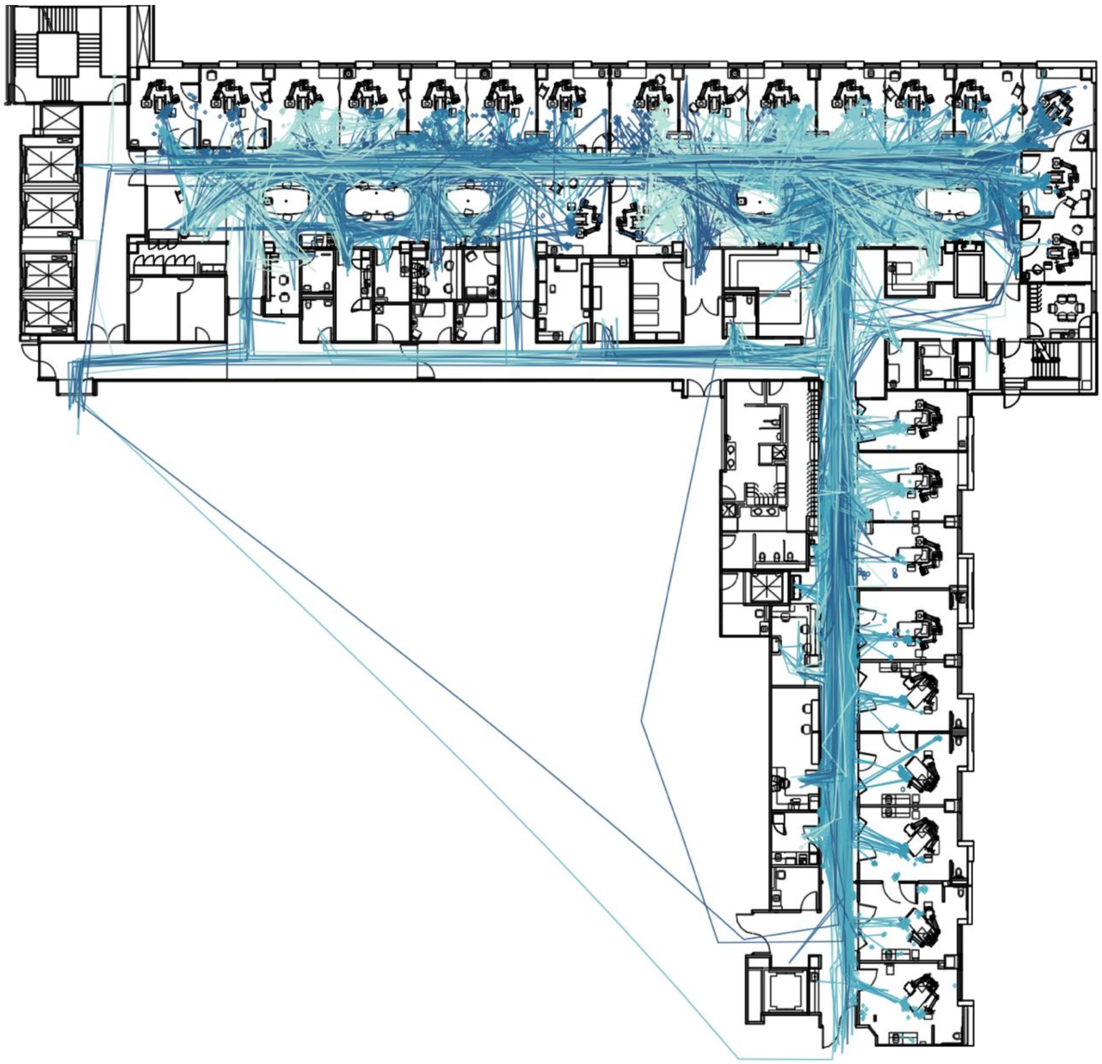


Figure 7 – Map of collected Activity and movement Data

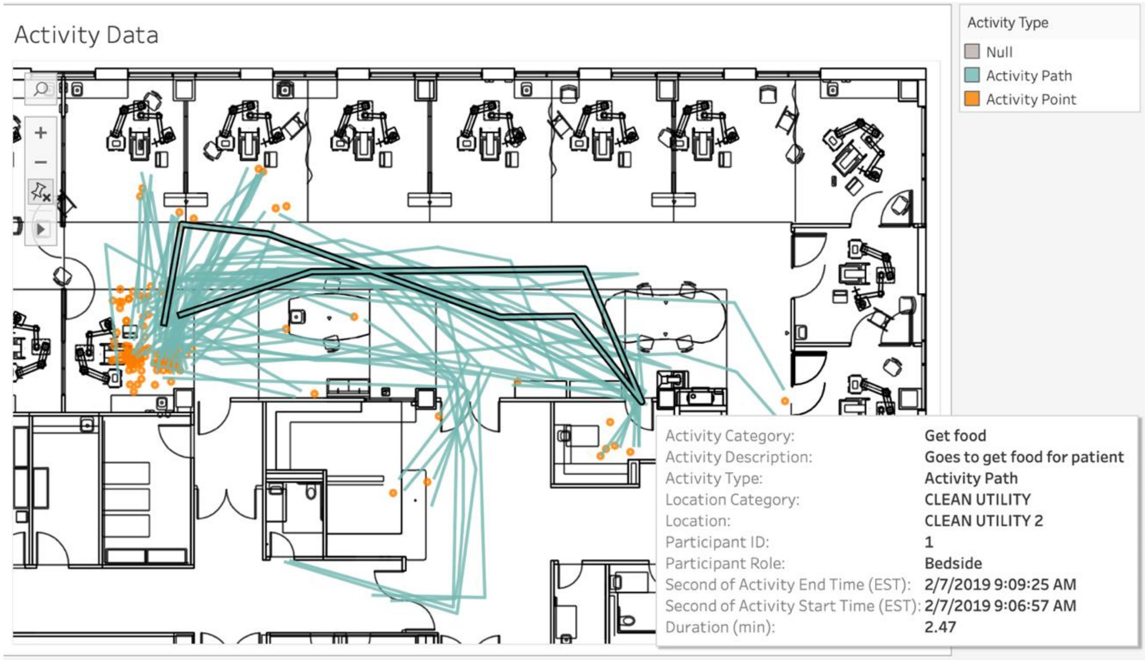


Figure 8 – Example of collected activity data for a bedside nurse

CHAPTER 3. FIELD STUDY

This chapter includes analysis of collected data through site observations to understand the structure and timing of nurses' activities and other care providers they interact with the CICU. This chapter aims to understand how nurses occupy the space for different activities, how they move within the unit to perform their daily tasks, and how they work and interact with other care providers in the CICU. It also presents a description of collected information on bedside nurses' interactions by exploring related implications for assessment of the study assumptions on the impact of layout features on interactions. The findings of this chapter are used to inform modeling strategy and simulation in this study and to interpret the simulation outputs.

3.1 CICU Key Locations

Nurse stations (NS): There are three nurse stations in Pod1 and two nurse stations in pod2. These nurse stations function as base stations for the charge nurse, resource nurses, respiratory therapists in pods 2 and 3, and care team members.

Respiratory station: The respiratory station is a nurse station in pod3, which is only used by the respiratory therapist assigned to pod3.

Workroom: The workroom is in pod 2. The care teams are based in the workroom, so bedside nurses and other care providers can reach them. All the attending doctors and advanced practice providers are assigned to this room. Most of them usually sit outside of the workroom because of the small size of the room, which does not fit everyone.

Decentralized nurse stations (DNS): Decentralized nurse stations are located between every two open patient rooms. Four of the open patient rooms (2103, 2108, 2109, and 2116) do not have decentralized nurse stations because of the design of the layout. Closed patient rooms do not have assigned decentralized nurse stations. Bedside nurses assigned to these rooms usually sit at mobile workstations outside rooms.

Clean utility rooms: Each of the pods has a clean utility room. There is a 4th clean utility room in the corridor outside the unit. Patients' nutrition, including baby food and milk, are kept in clean utility rooms at each pod. Breast milk is stored in the refrigerators inside clean utility rooms. Linen and clean sheets are also socked in the clean utility rooms, except for baby pillows that are in the supply closets.

Respiratory storage: The respiratory storage is in Pod 2. All the supplies and equipment related to respiratory care are in the respiratory closet. Since the respiratory closet is small, some respiratory equipment is kept in front of the storage or are kept inside patient rooms.

Supply closets: Each pod has a supply closet, that is kept stocked by a support technician. All the medical and patient care supplies are in these closets. If supply closets ran out of certain items, nurses get supplies from other pods. Some items also are stored in certain supply closets such as drain tubes and catheters, which are stocked in the supply closet in pod3.

Soiled utility rooms: All the soiled medical equipment is stored in the soiled utility room after being used. They are also used for disposing of patients' body fluids. There are three soiled utility rooms in the CICU. Two of them are in pods 2 and 3. The soiled utility room for pod 1 is outside the unit in the corridor.

Storage: There is one storage room located in the backstage corridor between pod 2 and 3, which is used for storing clean medical equipment and supplies.

Pneumatic Tube Systems: Each pod has a Pneumatic tube station which provides access to the tube system. These stations are used to send patient blood samples to the lab. They are also used for delivering some patient medications from the pharmacy. Once the medications are delivered to the tube station in pods, an alarm will go off at the station. Usually, one of the nurses picks up the medication from these stations and drop it off at the patient rooms.

Medication stations: Each pod has a Pyxis medication station. They contain patient medications, including pain medications and IV fluid pumps. Antibiotics and blood pressure medicine are usually delivered to the patient bedside by the pharmacist.

Staff break room: The staff break room is in pod 3, which is used by care providers during their break times.

3.2 CICU Structure

Multiple staff types work on the CICU unit, including bedside nurses, resources nurses, a charge nurse, advance practice providers, respiratory therapists, support technicians, and a pharmacist. Cardiology fellows and surgeons are not based on the unit but visit the unit frequently.

3.2.1 Nurses

Nurses are the main care provider group in the CICU. They have multiple roles and titles which change their utilization and responsibilities. They can be at bedside, resource, or charge nurse role. The assignment to any of these roles is based on their experience levels and credentials. Bedside nurses are responsible for direct patient care activities. Resource nurses are not assigned to any patients and support bedside nurses as needed. Charge nurses are responsible for the management of the unit, including nurse assignments, patient admissions, and patient transfers. There are 120 nurses who cover different shifts at the CICU. Only 15-20 of them work at the same time in the unit. Most nurses work either on day shift or night shift. A limited number of nurses rotate between the day and night shifts.

Bedside nurses start the work shift in the morning at 7:00 am. They usually arrive 15-30 minutes earlier to start the handoff with the nurse from the previous night shift. During the handoff process, the night shift nurse updates the day shift nurse about patient condition, medication, care routine, and events from the night before. If the day shift nurse works in consecutive days and has had the same patient in the previous day, the handoff duration becomes shorter.

The morning nurse huddle also happens around the same time, when all the nurses are gathered in the same location to get a quick update on patients and staffing for the day from the charge nurse. The nurse huddles are very short. Not all nurses participate in the huddles. Sometimes bedside nurses miss the huddle if they are involved in handoffs or patient care activities at that moment.

Bedside nurses also participate in surgery flash rounds early in the morning. Surgical flash rounds start at 7:00 am during the week, and 8:00 am on weekends. During the surgery flash rounds, team members from both care teams, resource nurses, the charge nurse, in addition to surgery staff from day shift and the previous night shift, visit the all the patient rooms to update the dayshift staff on patient status. During this time, nurses listen to the conversations and answer any questions that the team care members or surgeons might have.

After that, they start their care routine with cleaning the work surfaces, initial patient assessment, filling patient charts and performing any lab or medication orders that patients might have. For the rest of the day, they perform various activities including patient assessment, checking vital signs, medication administration, lab draws, patient nutrition, engaging with family members, participating in care team rounds, participating in respiratory rounds, working with other care providers, and assisting with procedures. They take a 30-minute break for lunch around noon. At the end of the day, around 7:00 pm, they handoff the patient to the night shift nurse.

There are two resource nurses on the unit for each working shift. If the total number of patients in the unit falls below 20, the unit might schedule only one resource nurse. Resource nurses are not assigned to any patients. They are responsible for helping bedside nurses and observing their patients while they are not on the bedside. Their activities, therefore, do not follow any patterns and are based on the needs of bedside nurses. They set up new patients in the room and help bedside nurses with patients coming from OR. Resource nurses are responsible for collecting unused medicine form patient rooms and returning to the pharmacy at the end of the shift, what they call “drug run”. They are also responsible for checking breast milk in the clean utility freezers to make sure they are not expired.

3.2.2 Respiratory Therapists

The total number of patients and their acuity levels determine the number of respiratory therapists that work on a unit in a single day. The total number of respiratory therapists for each shift is calculated by an algorithm based on patient treatment plans and respiratory equipment connected to patients. There are usually 3-4 respiratory therapist working on the unit, and each of them are responsible for 6-8 patients. If there are three respiratory therapists on the unit, each of them responsible for one of the three pods. If there are four respiratory therapists, they might cover patients from different pods, and they get assigned to consecutive rooms. Under any circumstances, there should always be two respiratory therapists in the unit. If one of the respiratory therapists want to leave the unit, they should make sure that there are two other therapists on the unit during their absence.

Respiratory therapists usually have three patient assessment rounds, one at 8:00 am, after the surgery flash rounds are done, one around noon and one around 4:00 pm. They also participate in the morning care team rounds. They are responsible for setting up incoming patients for ventilators, suction tubes, oxygen pumps, or other respiratory equipment. Respiratory therapists are responsible for giving inhale medications to patients. The help nurses in any patient care activity or procedure which are related to breathing or lunges. They can also sign off medication for bedside nurses. Respiratory therapists are also responsible for transferring patients who are on oxygen tanks. For their lunch break, they also get 30 minutes around noon.

3.2.3 Care Teams

Care team members arrive around 7:00 am or earlier to start handoff with care team members from the previous night shift. There are two care teams on the CICU unit (Blue team and Green team), each responsible for half of the patients on the unit. Rooms are divided between the two care teams based on the patient acuity levels. A team might get assigned to fewer number of patients with higher acuity levels. Once a patient gets assigned to an attending doctor, they follow their patients on the unit wherever their rooms are.

Each care team has one attending and a mid-level care provider or Advance Practice Provider (fellow, nurse practitioner, physician assistant). The Blue team usually has an attending and advance practice provider. The Green team usually has an attending and a cardiology fellow. During the week, there is usually one more attending doctor who floats between the two teams. Surgeons and the cardiology fellows visit the unit based if needed. There is one pharmacist in the CICU during the day shift who works Monday through Friday.

3.2.4 Patients

The incoming patients get assigned to bedside nurses based on their acuity levels and nurses' credentials for acuity handling. Patient room assignment is based on the equity level of patients in adjacent rooms and room availability. The electronic system tracks direct patient cares hours based on the nurses' input in the system. If they are between 5-6 hours, the patient gets assigned to a bedside nurse with two patients. If the direct care hours are more than that, the patient gets assigned to a nurse with the one-patient assignment.

Patient acuity and condition determine the care process depending on patient admission reason to the CICU, sedation status, infections, diets, medication orders, and required procedures. Patients might get admitted to the CICU for a variety of reasons, including pre-operation of a cardiac surgery, post-operation of cardiac surgeries, post-operation of non-cardiac surgeries, post-cardiac catheterization, evaluation of structural heart disease, medical condition or ICU overflow.

Post-operation patients might be sedated and, therefore, be fed through IVs. In this case, the bedside nurse assigned to them would not go through the standard process of getting food, preparing food, and feeding the patient. After sedation, they would start getting milk of food depending on their condition. Post-operation patients usually are assigned to a bedside nurse with a one-patient assignment to monitor their status closely. The status of post-operation patients gets examined through Echocardiogram (ECHO), Ultrasound, X-ray, or Electrocardiogram (EKG).

After post-operation patients become stable, specialized therapists such as physical therapists, occupational therapists, and lactation therapists work with patients to prepare them for discharge and regular care. Post-operation patients might be intubated and connected to a chest tube or urine tube. In this case, the bedside nurses should check the tubes regularly (usually every hour). The assigned physicians decide whether the tube needs to be changed or removed through intubation or extubating procedures. If the patient is connected to a urine tube, the bedside nurse empties the tubes when full in the soiled utility rooms. Post-op or pre-op patients might get a procedure for a straight catheter by their assigned care team if required. They might also get other procedures for changing lines or tubes depending on their condition.

If patients have infections or have other issues related to their immune systems, they get assigned to one of the private patient rooms that can be closed off. At the entrance to the patient rooms with infected patients, a cabinet with gowns, gloves, and mask will be located so everyone can put them one before entering the rooms. The analysis of the CICU historical data showed that 8% of the admitted patients to the CICU had some sort of infection. The CICU patients connected to Extra Corporeal Membrane Oxygenation (ECMO) require extensive care. They get assigned to 2 bedside nurses and are visited frequently by their assigned care team members.

According to the historical patient data, the age of the admitted patients varied between 0 and 7,909 days (21-years old), with a median of 216 days (7-months old). Most patients were admitted to the CICU right after birth (0-day old) with 54% of the records. Most patients admitted to the CICU aged under one year (59%). Patients aged between 61 days and four years fell within 25% and 75% percentiles and constituted the most common age group admitted to the CICU.

The importance of patient age for the current study is in the way that it changes the care processes for bedside nurses. Patients younger than one-year-old usually are fed formulas or breast milk, whereas older patients can eat food. Bedside nurses get the milk from the clean utility rooms and prepare it in the patient rooms and feed it to the patients.

For older patients, they order food from the hospital's kitchen, and the food will be brought over by a staff member. In this case, bedside nurses help patients eat and then return the dishes.

The other implication of patient age is the process of using the bathroom. Younger patients are on diapers, whereas older patients use a bedside toilet or are connected to a catheter if they are very ill. If patients are on diaper, it requires the bedside nurse to take several trips to supply closets to get a diaper and change the diapers occasionally. For older patients, if they use a bedside toilet seat, the bedside nurse would get the seat from the storage, help them use the toilet, and then return the seat and soiled items to the soiled utility rooms.

Newborn patients are significantly different from other age groups because of their unique needs. Every time that a family member of a newly born patient visits, bedside nurses would help them with the kangaroo care process by providing a comfortable chair, getting sheets and pillows from clean utility rooms, helping the family members to hold the baby and then returning the baby to the bed.

Based on the CICU historical data, there are three admissions and three discharges per day on average. The number of admissions and discharges during the day can vary between 1 and 4. By looking at the CICU admission reasons, most admitted cases are post-operation cardiothoracic surgery patients (41%), patients with cardiac medical conditions (35%), and pre-operation cardiothoracic patients (15%). The stay duration of patients in the CICU ranged from 1 to 734 days.

3.3 Field Data Analysis Methods

The collected activity and movement data from the study site are analyzed to understand how bedside nurses and other care providers occupy different areas for various activities. The results of the data analysis are later used in the simulation to assign bedside nurses' base locations for different categories of activities.

This study assumes that bedside nurses' movements, spatial occupancy, and activities are determined by patient needs, patient care activities and nurses' workflow. In order to understand if other factors such as bedside nurses' assigned locations, and number of patients played a role in their spatial occupancy, bedside nurses' time at different locations are compared across pods (pod1, pod2, and pod3) and for one and two-patient assignments. Generalized linear models are used to compare counts of visiting each location across different categories. An analysis of variance test is used to compare the duration of time at each location for nurses in pod1, pod2, and pod3. A t-test is used to compare the duration of time at each location for nurses assigned to one or two patients.

Bedside nurses' travel paths are also analyzed to understand how they move within their assigned pods and to other areas within the CICU unit to perform their activities. This information is used to identify bedside nurses' movement strategies to inform the simulation modeling. For each agent representing a care provider in the simulation model, the movement paths to various destinations will be assigned based on the observation data.

Bedside nurses' interaction data is also analyzed to understand the dynamics of bedside nurses' interactions. The interaction data analyzed in this chapter is used for two purposes. First, it has been used to understand how bedside nurses interacted with each group of care providers. The analysis of bedside nurses' interaction data helps answer questions such as where interactions happen, who they interact with, and which activities require them to interact. The answers to these questions will be used to model bedside nurses' planned interactions in simulation. Second, it has been used to test the assumptions of this study about using simulation modeling to evaluate the impact of design on the occurrence of encounters. The counts of bedside nurses' interactions in pod1, pod2, and pod3 are compared using generalized linear models to understand if bedside nurses' location assignment is associated with the occurrence of interactions.

3.4 Bedside Nurses' Locations

3.4.1 Bedside Nurses' Time Spent at Different Locations

Table 3 shows the sum duration of time spent at each location category per observation period for each bedside nurse. For all locations other than assigned patient rooms and assigned decentralized nurse stations, the recorded time includes time at those locations, in addition to the time spent to get to those locations. Based on the results of the data analysis, bedside nurses spent the most time at their assigned patient rooms and decentralized nurse station. If bedside nurses did not have any assigned decentralized nurse stations, they spent most of their times at their assigned patient rooms. In case of observation 1 and 4, the bedside nurses were assigned to patient rooms 2109 and 2103 which do not have assigned decentralized nurse station.

During the working shift, beside nurses spent 303.6 minutes at their assigned patient room (PT RM ASSIGNED), 290.7 minutes at their assigned decentralize nurse station (DNS ASSIGNED), 26.6 at staff break room or toilets, 26.5 minutes outside the unit (for breaks, patient transfers or other purposes), 18.5 minutes at unassigned patient rooms (PT RM UNASSIGNED) or decentralized nurse stations (DNS UNASSIGNED), 10.7 minutes at Pyxis medication stations(MED), supply closes (SUPPLY), and pneumatic tube station (PNEUMATIC), 9 minutes at central nurse stations (NS), respiratory station (RESP STATION) and care team workroom (WORK RM), 7.1 minutes at clean utility rooms (CLEAN UTILITY), equipment or respiratory storage (STORAGE) and soiled utility rooms (SOILED UTILITY), 3.8 minutes at corridors, 1.2 minutes at laundry (LAUNDRY) or handwashing stations (HW) in average.

Based on the above analyses, bedside nurses spent almost 82% of their working shifts at their assigned patient rooms or decentralized nurse stations, 15% at other locations within the CICU, and 3% of their time out of the CICU unit in average.

Bedside nurses' time spent at different locations in the CICU depended on individual patient's needs and nurses' activities. In order to understand if other explanatory variables influenced the bedside nurses' time spent at different locations, the associations between bedside nurses assigned locations (pod1, pod2, and pod3) and the number of assigned patients (one or two) with the time spent at each location are explored.

A one-way analysis of variance is used to test if the bedside nurses' location (pod1, pod2, and pod3) as an explanatory variable was related to the duration of time spent at different locations. The comparison between bedside nurses' in pod1, pod2, and pod3 did not show any significant difference between the time spent at different locations among the three groups (Table 4).

A t-test is used to assess if the bedside nurses' assignment (one-patient and two-patient) as another explanatory variable was related to the duration of time spent at different locations. The comparison between bedside nurses in the two groups did not show any significant differences in the time they spent at various locations, except for centralized nurse stations. Bedside nurses assigned to only one patient (Mean=9.62 minutes, SD=3.93), compared to those assigned to two-patients (Mean=3.96 minutes, SD=3.46) spent significantly more time at the centralized nurses stations ($t(9.28)=2.95$, $p<0.05$). This observed difference can be explained by the fact that they are responsible for patients with critical conditions and more frequently consult with other care providers based in the central nurse stations.

Table 3 - Bedside nurses' time spent at different locations

	Observation																
Location Category	1	2	4	5	6	7	8	9	10	12	13	14	15	16	17	18	19
CLEAN UTILITY	17.7	3.7	10.9	5.2	3.9	7.8	8.8	2.3	5.4	2.8	2.9	2.2	6.4	10.4	10.4	8.1	2.9
CORRIDOR		14.6	3.7	3.7	1.2	2.4	2.9		7.3	0.7	3.0	1.9	4.3	4.1		0.2	
DNS ASSIGNED		344.2		294.5	275.6	287.6	209.4	315.6	317.4	365.9	289.5	420.6	329.4	37.2	250.4	381.3	242.3
DNS UNASSIGNED	7.3		1.8		7.8	3.5		4.0	1.1	0.9	14.1	10.1		3.2	4.2		
HW									0.6	2.8							
LAUNDRY			2.1		0.4	0.4			1.3				0.3	0.4			
MED	2.4	2.9	9.6	7.6	4.8	4.4	4.7	1.4	8.5	8.1	4.8	4.0	2.9	3.4	9.6	7.3	5.5
NS	7.6	4.5	10.7	10.3	16.3	8.4	1.1	3.1	4.4	1.3		0.8	11.1	5.1	2.0	7.6	6.2
OUTSIDE UNIT	43.4	31.3			36.7	41.3	24.2	31.5	64.0	1.7	2.5	2.8			29.2	33.8	1.7
PNEUMATIC	0.3	2.5	2.4	2.0			0.9			0.4		1.4	0.4	1.9	2.1	1.0	
PT RM ASSIGNED	575.4	230.5	561.5	200.8	277.4	243.3	357.4	245.6	238.9	187.1	301.3	206.7	210.0	546.2	330.8	142.9	305.0
PT RM UNASSIGNED	18.0	8.6	3.0	9.3	21.4	31.3	16.8	6.7	5.6	8.0	14.7	8.6	42.7	9.2	2.9	49.3	1.0
RECEPTION	7.7		1.6	2.6	2.3	1.9	2.6	0.4	3.5				0.3	2.8	2.9	0.9	1.5
RESP STATION					0.8		0.3		1.2	11.8	0.8						
SOILED UTILITY				3.1					1.6					0.9			
STAFF BREAK RM				47.7			0.7	3.2	2.8	45.9	36.9	30.6	29.1	31.9	37.3	12.6	66.6
STORAGE				0.6				0.8	1.4	0.5							
SUPPLY	6.0		8.4	3.9	3.7	4.4	4.4	2.2	2.1	4.8	7.1		4.1	6.6	7.3	6.1	3.9
TOILET	4.0	5.8	6.3	21.4	2.5	6.4	10.7	11.9		8.7		1.8	10.3	2.6		13.4	1.6
WORK RM					4.3										2.2	0.6	

SUM(DurationMinutes)

0.2 575.4

Table 4 – Comparison of bedside nurses' time at different locations by pods

	Analysis of Variance						Mean for One-way Anova				
Location	Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F	Level	Mean	Std Error	Lower 95%	Upper 95%
CLEAN UTILITY	Pod	2	57.081	28.54	1.81	0.19	1	8.07	1.98	3.8	12.31
	Error	14	219.78	15.69			2	7.32	1.32	4.4	10.16
	C. Total	16	276.86				3	3.29	1.98	-0.95	7.54
CORRIDORS	Pod	2	20.99	10.49	0.77	0.48	1	0.95	1.84	-3.00	4.90
	Error	14	190.31	13.59			2	3.67	1.22	1.03	6.30
	C. Total	16	211.31				3	3.23	1.84	-0.72	7.18
DNS ASSIGNED	Pod	2	44448.53	22224.3	1.43	0.27	1	218.49	62.12	85.25	351.73
	Error	14	216126.9	15437.6			2	232.610	41.416	143.7	321.44
	C. Total	16	260575.4				3	348.06	62.12	214.8	481.30
DNS UNASSIGNED	Pod	2	56.74	28.37	1.79	0.20	1	1.49	1.98	-2.76	5.75
	Error	14	220.95	15.782			2	2.85	1.324	0.01	5.69
	C. Total	16	277.70				3	6.54	1.98	2.25	10.80
HW	Pod	2	2.17	1.08	2.92	0.08	1	0	0.30	-0.65	0.65
	Error	14	5.19	0.37			2	0	0.20	-0.43	0.43
	C. Total	16	7.36				3	0.84	0.30	0.18	1.49
LAUNDRY	Pod	2	0.37	0.18	0.52	0.60	1	0.53	0.29	-0.10	1.16
	Error	14	4.96	0.35			2	0.16	0.19	-0.26	0.59
	C. Total	16	5.33				3	0.32	0.29	-0.31	0.96
MED	Pod	2	28.49	14.24	3.63	0.05	1	6.50	0.98	4.38	8.62
	Error	14	54.80	3.91			2	3.82	0.65	2.41	5.24
	C. Total	16	83.29				3	6.32	0.98	4.20	8.44
NS	Pod	2	101.34	50.67	3.22	0.07	1	6.65	1.98	2.39	10.9
	Error	14	220.31	15.73			2	7.59	1.32	4.75	10.42
	C. Total	16	321.65				3	1.61	1.98	-2.63	5.87
PNEUMATIC	Pod	2	1.64	0.82	0.91	0.42	1	1.33	0.47	0.31	2.35
	Error	14	12.67	0.90			2	0.89	0.31	0.21	1.57
	C. Total	16	14.32				3	0.43	0.47	-0.59	1.45
PT RM ASSIGNED	Pod	2	230.68	115.34	0.56	0.58	1	335.06	68.35	188.4	481.68
	Error	14	2873.08	205.22			2	320.64	45.57	222.9	418.39
	C. Total	16	3103.77				3	233.47	68.35	86.86	380.09
PT RM UNASSIGNED	Pod	2	230.68	115.34	0.56	0.58	1	14.04	7.16	-1.31	29.40
	Error	14	2873.08	205.22			2	18.21	4.77	7.97	28.45
	C. Total	16	3103.77				3	9.20	7.16	-6.15	24.56
RESP STATION	Pod	2	34.60	17.30	2.57	0.11	1	0	1.29	-2.77	2.77
	Error	14	93.95	6.71			2	0.11	0.86	-1.73	1.96
	C. Total	16	128.56				3	3.44	1.29	0.66	6.22
SOILED UTILITY	Pod	2	0.58	0.29	0.38	0.69	1	0	0.43	-0.93	0.93
	Error	14	10.66	0.76			2	0.45	0.29	-0.17	1.07
	C. Total	16	11.25				3	0.39	0.43	-0.54	1.32
STAFF BREAK RM	Pod	2	1162.36	581.18	1.27	0.30	1	29.11	10.66	6.23	51.99
	Error	14	6373.96	455.28			2	12.51	7.11	-2.74	27.76
	C. Total	16	7536.32				3	29.04	10.66	6.15	51.92
STORAGE	Pod	2	0.48	0.24	1.7	0.21	1	0	0.18	-0.40	0.40
	Error	14	1.95	0.13			2	0.14	0.12	-0.11	0.41
	C. Total	16	2.44				3	0.47	0.18	0.07	0.87
SUPPLY	Pod	2	19.64	9.82	2.036	0.16	1	6.39	1.09	4.04	8.75
	Error	14	67.51	4.82			2	3.90	0.73	2.33	5.47
	C. Total	16	87.15				3	3.76	1.09	1.41	6.12
WORK RM	Pod	2	1.08	0.54	0.38	0.68	1	0.71	0.59	-0.56	1.99
	Error	14	19.91	1.42			2	0.48	0.39	-0.37	1.33
	C. Total	16	20.99				3	0	0.59	-1.27	1.27

Table 5 – Comparison of bedside nurses' time at different locations by assignment (one or two patients assigned)

	Analysis of Variance		t-Test					Mean				
Location	**F ratio**	**Prob >F**	**t**	**DF**	**Sig. (2-tailed)**	**Mean Difference**	**Std Err Diff**	**Level**	**Mean**	**Std Error**	**Lower 95%**	**Upper 95%**
CLEAN UTILITY	1.46	0.24	2.51	15	0.24	2.51	2.08	One	8.18	1.67	4.61	11.75
								Two	5.66	1.23	3.03	8.3
CORRIDOR	1.23	0.28	1.11	15	0.28	2.03	1.83	One	4.24	1.47	1.10	7.38
								Two	2.20	1.08	0.11	4.52
DNS ASSIGNED	1.89	0.18	1.37	15	0.18	86.76	63.03	One	200.3	50.7	92.25	308.3
								Two	287.0	37.4	207.26	366.8
DNS UNASSIGNED	0.002	0.98	0.01	15	0.98	0.03	2.18	One	3.38	1.75	0.36	7.12
								Two	3.41	1.22	0.64	6.17
HW	0.78	0.39	0.88	15	0.39	0.3	0.34	One	0	0.27	0.59	0.59
								Two	0.3	0.2	0.13	0.74
LAUNDRY	1.13	0.3	1.06	15	0.3	0.31	0.29	One	0.49	0.23	0.01	0.99
								Two	0.17	0.17	0.19	0.54
MED	0.08	0.77	0.29	15	0.77	0.35	1.19	One	5.27	0.95	3.23	7.31
								Two	4.92	0.77	3.541	6.43
NS	9.46	0.0077	5.66	9.2	0.01	5.66	1.91	One	9.62	1.6	5.49	13.7
								Two	3.96	1.04	1.64	6.29
PNEUMATIC	0.95	0.34	0.97	15	0.34	0.47	0.48	One	1.19	0.38	0.37	2.01
								Two	0.72	0.28	0.11	1.33
PT RM ASSIGNED	1.02	0.32	1.01	15	0.32	68.98	68.02	One	348.1	54.71	231.5	464.7
								Two	279.1	40.41	193.05	365.3
PT RM UNASSIGNED	0.001	0.97	0.03	15	0.97	0.23	7.4	One	15.2	5.87	2.74	27.7
								Two	15.03	4.33	5.88	24.2
RESP STATION	0.62	0.44	0.78	15	0.44	1.14	1.45	One	0.12	1.17	2.36	2.62
								Two	1.27	0.86	0.56	3.12
SOILED UTILITY	0.46	0.5	0.68	15	0.5	0.29	0.43	One	0.52	0.34	0.22	1.26
								Two	0.22	0.25	0.32	0.77
BREAK RM	3.46	0.08	1.86	15	0.08	19.09	10.25	One	7.95	8.24	9.62	25.53
								Two	27.04	6.09	14.06	40.02
STORAGE	0.51	0.48	0.71	15	0.48	0.14	0.2	One	0.09	0.16	0.24	0.44
								Two	0.24	0.11	0.01	0.49
SUPPLY	0.007	0.93	0.08	15	0.93	0.1	1.22	One	4.39	0.98	2.29	6.48
								Two	4.44	0.72	2.94	6.04
WORK RM	0.61	0.44	0.78	15	0.44	0.46	0.58	One	0.72	0.47	0.28	1.72
								Two	0.24	0.34	0.48	1.00

3.4.2 Bedside Nurses' Counts of Visiting Different Location

Table 6 shows the frequency of visiting different locations from assigned patient rooms or decentralized nurse stations for each observation session of bedside nurses. The most visited locations are unassigned patient rooms with average 11.12 times, centralized nurse stations with 7.58 times, clean utility rooms with 6.76 times, Pyxis medication stations with 6.52 times, supply closets with five times and unassigned nurse stations with

3.70 times during an observed shift. All other locations had average visiting frequencies below two times. Based on these frequencies, most bedside nurses' movements are for helping or interacting with other bedside nurses, interacting or consulting with other care providers, getting food, medication, and supplies.

Table 6 - Counts of visiting different locations by bedside nurses

Location Counts

	Observation																
Location Category	1	2	4	5	6	7	8	9	10	12	13	14	15	16	17	18	19
CLEAN UTILITY	17	5	18	6	7	14	11	4	7	2	2	3	8	13	10	5	4
CORRIDOR		3	3	7	6	3	6		4	1	3	1	3	3		1	
DNS ASSIGNED		104		148	92	115	106	92	109	135	108	104	146	24	99	144	89
DNS UNASSIGNED	9		7		11	4		2	1	1	13	11		4	9		
HW									2	6							
LAUNDRY			2		1	1			2				1	1			
MED	3	9	18	18	10	6	10	2	6	22	10	6	6	5	10	12	5
NS	7	7	10	19	27	8	2	5	7	1		2	25	10	5	9	9
OUTSIDE UNIT	2	2			2	2	1	1	4	1	1	1			1	1	1
PNEUMATIC	1	3	2	1			1			1		2	1	2	3	1	
PT RM ASSIGNED	178	107	312	115	131	141	158	152	177	155	168	79	146	378	190	117	159
PT RM UNASSIGNED	21	12	6	13	20	16	17	11	5	7	16	4	41	15	7	17	2
RECEPTION	8		2	5	3	4	5	1	2				1	5	2	1	1
RESP STATION					1		1		1	10	1						
SOILED UTILITY				2					1					1			
STAFF BREAK RM				5			2	1	2	6	2	1	1	1	1	1	2
STORAGE				1				1	1	1							
SUPPLY	4		12	4	5	8	8	4	3	5	6		7	10	6	4	3
TOILET	2	5	12	11	3	1	2	3		2		1	2	1		3	1
WORK RM					3										2	1	

Bedside nurses' visit counts of different locations in the CICU depends on patient's needs and the individual nurses' preferences. A Generalized Linear Model (GLM) is used to test if other explanatory factors such as bedside nurses' location or patient assignments were related to the visit counts. Generalized Linear Models can show the relations between count data as the response variable and discrete or continuous explanatory variables. The results of the GML model with a Poisson distribution for the response variable and a logarithmic link function of explanatory variables did not show any significant influences in visit counts of different locations based on bedside nurses' pod assignment (pod1, pod2, and pod3) in most key locations.

Table 7 shows the estimation results from the fitted GML for visit counts to different locations as response variables based on bedside nurses' assigned pods. Bedside nurses in pod3 visited the clean utility room significantly less frequently compared to those in pod2 and pod3. Most patients in pod3 did got nutrition through food tubes or did not eat. For this reason, the bedside nurses in this pod visited the clean utility room less frequently to get milk. Bedside nurses in pod2 visited the centralized nurse stations significantly more frequently compared to those located in pod3 and pod1. Three of the five nurse stations are in pod2, which can explain this difference. Bedside nurses in pod3 also visited other unassigned patient rooms less frequently compared to those located in pod2 and pod since their assigned locations isolated them from bedside nurses in other pods.

The results of the GML model with a Poisson distribution for the response variable and a logarithmic link function of explanatory variables did not show any significant influences in visit counts of most key locations based on bedside nurses' patient assignment (one or two). Table 8 shows the estimation results from the fitted GML for visit counts to different locations based on one or two assigned patients. Bedside nurses assigned to only one patient visited the central nurse stations more frequently compared to those assigned to two patients, in order to consult with other care providers.

Table 7 – The GML results for bedside nurses' visit counts to other locations by pod

	Parameter	Estimate	Std error	L-R chi square	Prob > Chi square	Lower CR	Upper CR
CLEAN UTILITY	Intercept	1.9076044	0.1106648	123.84011	<.0001*	1.6780669	2.1138271
	Pod[1]	0.3170191	0.1457934	4.640139	0.0312*	0.0289685	0.6038939
	Pod[2]	0.3378222	0.1271545	7.5112549	0.0061*	0.0944521	0.5952268
DNS UNASSIGNED	Intercept	1.4873564	0.1221542	89.141572	<.0001*	1.237028	1.7169628
	Pod[1]	-0.101062	0.1890899	0.2936109	0.5879	-0.493458	0.2530386
	Pod[2]	-0.283384	0.1613467	3.1160211	0.0775	-0.604398	0.031246
HW	Intercept	-12.41459	2634.1928	15.347828	<.0001*	-284.9503	-1.073965
	Pod[1]	-6.553868	4620.6799	1.5878e-5	0.9968	-305.4033	247.65917
	Pod[2]	-6.553868	3652.9681	2.0529e-5	0.9964	-130.5212	242.06501
LAUNDRY	Intercept	-0.732408	0.372678	5.0914121	0.0240*	-1.575881	-0.085452
	Pod[1]	0.039261	0.5527708	0.0050002	0.9436	-1.249675	1.0534135
	Pod[2]	-0.078522	0.4714045	0.0277297	0.8677	-1.039835	0.8827907
MED	Intercept	2.2850485	0.0812693	403.12688	<.0001*	2.1212475	2.4400787
	Pod[1]	0.1353197	0.1183727	1.2699031	0.2598	-0.10279	0.3624884
	Pod[2]	-0.248167	0.1069374	5.4395584	0.0197*	-0.459587	-0.039531
NS	Intercept	1.8432532	0.1244517	86.388853	<.0001*	1.5804574	2.0719505
	Pod[1]	0.26696	0.1599663	2.7907369	0.0948	-0.046545	0.5859515
	Pod[2]	0.6600025	0.1360828	28.592251	<.0001*	0.4046985	0.9419791
PNEUMATIC	Intercept	0.039261	0.2605787	0.0223431	0.8812	-0.534174	0.5038064
	Pod[1]	0.3662041	0.3513642	1.0405687	0.3077	-0.360108	1.0563063
	Pod[2]	-0.039261	0.3239418	0.0146605	0.9036	-0.678591	0.6204245
PT RM UNASSIGNED	Intercept	2.3578821	0.087257	322.24362	<.0001*	2.1803904	2.5229625
	Pod[1]	-0.278441	0.1342775	4.5932445	0.0321*	-0.551637	-0.023169
	Pod[2]	0.5568811	0.0980909	35.63156	<.0001*	0.3683777	0.7535971
RESP STATION	Intercept	-5.89154	937.12679	6.6130374	0.0101*	-249.0672	-0.24677
	Pod[1]	-11.37762	1874.2535	5.2753138	0.0216*	-496.5028	-0.25325
	Pod[2]	4.387463	937.12688	0.1235716	0.7252	-1.699384	247.31692
SOILED UTILITY	Intercept	-6.977275	1688.676	15.924047	<.0001*	-249.9719	-0.822559
	Pod[1]	-11.46964	3377.3519	1.9452036	0.1631	-496.2974	0.5795608
	Pod[2]	5.8786629	1688.676	1.6745595	0.1956	-0.527213	242.6501
BREAK RM	Intercept	0.3723205	0.2213366	2.4228038	0.1196	-0.107152	0.7715859
	Pod[1]	-0.37232	0.3637626	1.1837959	0.2766	-1.193664	0.2717653
	Pod[2]	-0.26696	0.2869203	0.8620288	0.3532	-0.84211	0.304233
STORAGE	Intercept	-6.881381	1688.676	15.211102	<.0001*	-249.878	-0.767122
	Pod[1]	-11.56554	3377.3519	2.3014565	0.1293	-496.3432	0.409802
	Pod[2]	5.3773038	1688.676	0.5694565	0.4505	-1.146466	242.80245
SUPPLY	Intercept	1.6000476	0.1208436	92.830211	<.0001*	1.350798	1.8260945
	Pod[1]	0.2325338	0.1671422	1.873992	0.1710	-0.103318	0.5560553
	Pod[2]	0.1147508	0.1458418	0.6250546	0.4292	-0.168429	0.405839
WORK RM	Intercept	-6.475916	1378.7981	11.537027	0.0007*	-249.4081	-0.55228
	Pod[1]	6.188234	1378.7982	3.7808517	0.0518	-0.011394	249.08786
	Pod[2]	5.3773038	1378.7982	0.8541848	0.3554	-0.822324	197.65132

Table 8 – The GML results for bedside nurses' visit counts to other locations by patient assignment

	Parameter	Estimate	Std error	L-R chi square	Prob > Chi square	Lower CR	Upper CR
CLEAN UTILITY	Intercept	2.1245722	0.0857586	338.19274	<.0001*	1.9516437	2.2880753
	Pt Assi.[One]	0.288361	0.0857586	11.122093	0.0009*	0.1197423	0.4567018
DNS UNASSIGNED	Intercept	1.4789523	0.1190045	98.281857	<.0001*	1.2360634	1.7033263
	Pt Assi.[One]	0.1632755	0.1190045	1.8464171	0.1742	-0.073567	0.3950534
HW	Intercept	-10.31433	5250.4783	12.385394	0.0004*	-266.6675	-0.675434
	Pt Assi.[One]	-9.995875	5250.4783	6.9650891	0.0083*	-94.42888	-0.349077
LAUNDRY	Intercept	-0.708533	0.3535534	5.1596255	0.0231*	-1.49164	-0.087181
	Pt Assi.[One]	0.3030679	0.3535534	0.7238207	0.3949	-0.417917	1.0240524
MED	Intercept	2.2562616	0.0810298	394.38138	<.0001*	2.0929556	2.4108488
	Pt Assi.[One]	0.1108621	0.0810298	1.8423167	0.1747	-0.049892	0.2684152
NS	Intercept	2.2422711	0.0808608	412.19642	<.0001*	2.079486	2.3966759
	Pt Assi.[One]	0.3226783	0.0808608	15.720305	<.0001*	0.1640267	0.481659
PNEUMATIC	Intercept	0.0770753	0.2417469	0.0989598	0.7531	-0.440092	0.5149639
	Pt Assi.[One]	0.0770753	0.2417469	0.1004066	0.7513	-0.422796	0.5429531
PT RM UNASSIGNED	Intercept	2.6217546	0.0678342	677.69423	<.0001*	2.4856082	2.7516791
	Pt Assi.[One]	0.0638228	0.0678342	0.8758958	0.3493	-0.070715	0.195589
RESP STATION	Intercept	-0.812353	0.5188745	4.016469	0.0451*	-2.262754	-0.014331
	Pt Assi.[One]	-0.979407	0.5188745	6.1962557	0.0128*	-2.428934	-0.172656
SOILED UTILITY	Intercept	-1.40168	0.5	13.282712	0.0003*	-2.571413	-0.558789
	Pt Assi.[One]	0.3030679	0.5	0.3619103	0.5474	-0.756897	1.363033
BREAK RM	Intercept	0.2077577	0.25	0.6289291	0.4277	-0.346336	0.6504998
	Pt Assi.[One]	-0.390079	0.25	2.8071404	0.0938	-0.940228	0.0618499
STORAGE	Intercept	-1.545521	0.5773503	14.083335	0.0002*	-3.065132	-0.617694
	Pt Assi.[One]	-0.246238	0.5773503	0.196135	0.6579	-1.749244	0.7813122
SUPPLY	Intercept	1.6661023	0.1097271	134.28866	<.0001*	1.4424323	1.873289
	Pt Assi.[One]	0.0386458	0.1097271	0.1231943	0.7256	-0.181266	0.250553
WORK RM	Intercept	-0.996215	0.4082483	8.5415726	0.0035*	-1.918877	-0.289971
	Pt Assi.[One]	0.3030679	0.4082483	0.5428655	0.4612	-0.540379	1.146515

3.5 Bedside Nurses' Trips from Patient Rooms

Understanding the travel path patterns within the unit can be useful for modeling the movement strategies for studying the occupancy patterns in the unit. The analysis of collected data on bedside nurses' movement paths from patient rooms (both from patient bedside and assigned workstation) shows that they left the patient area mostly to gather supplies constituting 20.21% of all trips. After supply gathering, the most common reasons for taking trips from patients' areas were interactions (16.1%), medication delivery (15.09%), helping other nurses (13.25%), breaks (11.02%), and nutrition delivery (10.76%). Other care-related trips from patient room areas included trips for blood work (4.07%), trips for getting equipment (2.62%), and soiled items disposal (1.31%).

Some categories of the trips happened locally, meaning that these paths were traveled between the patient rooms and immediately accessible spaces in the same pod (Figure 9). Examples of these paths are medication delivery, nutrition delivery, blood work, and helping other nurses. Each pod has an assigned medication station, clean utility rooms (where patients' food is stored), and pneumatic tube systems. Bedside nurses use these locations in their pods as needed and usually do not travel to other pods for such activities. They are also most likely to help other bedside nurses in their neighborhood than others.

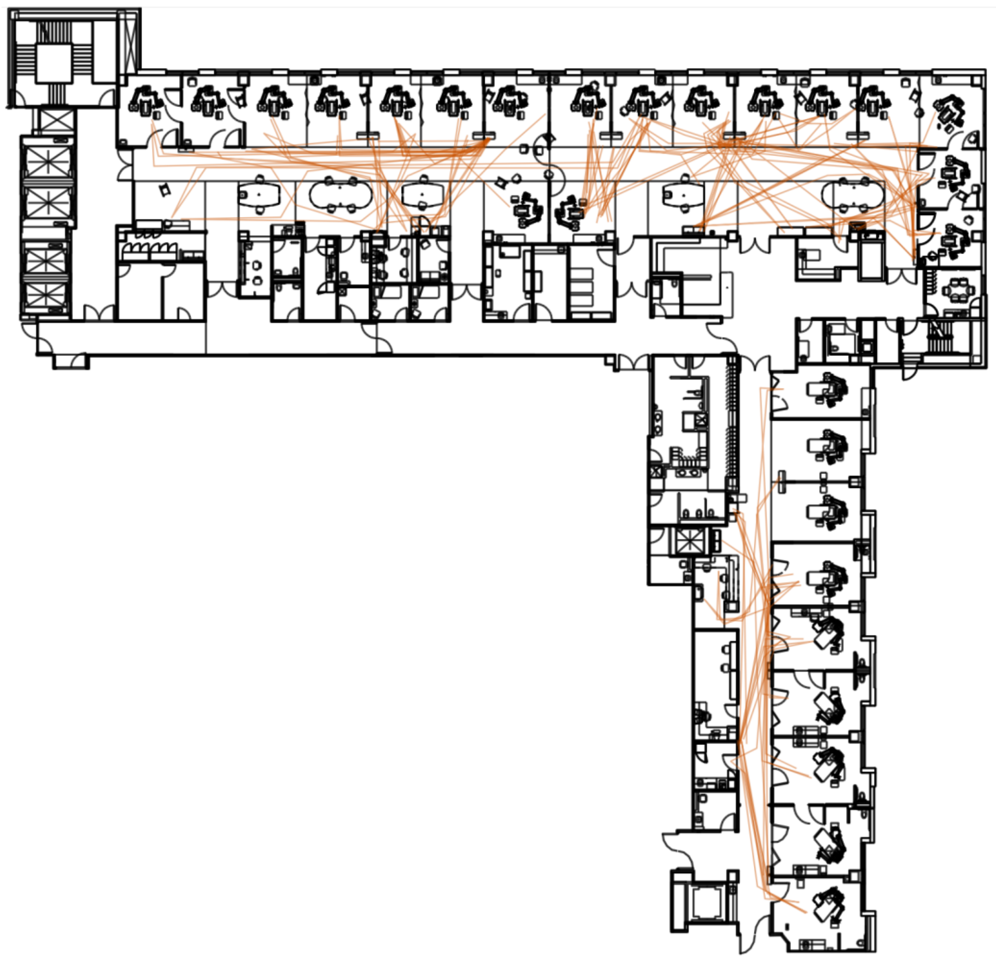


Figure 9 – Bedside nurses' local travel paths to help others

Some of the observed travel paths had a global scale where bedside nurses traveled to other pods to perform these activities, as well as within their assigned pods. Examples of these travel paths are gathering supply or equipment, interactions, breaks, or soiled disposals. Although each pod has a supply closet, bedside nurses still travel to other pods to get some supplies since some supplies are stored only at specific closets. Storage areas are scattered across the entire unit, and bedside nurses usually travel outside their assigned area to get the required equipment. In cases that bedside nurses need to consult with care team members, they go and find them if they are not located in their assigned pod. Therefore, travel paths for interactions have a global scale. The break room is in pod3, and nurses from all three pods travel there to take breaks. They also travel to different pods to use any available bathroom.

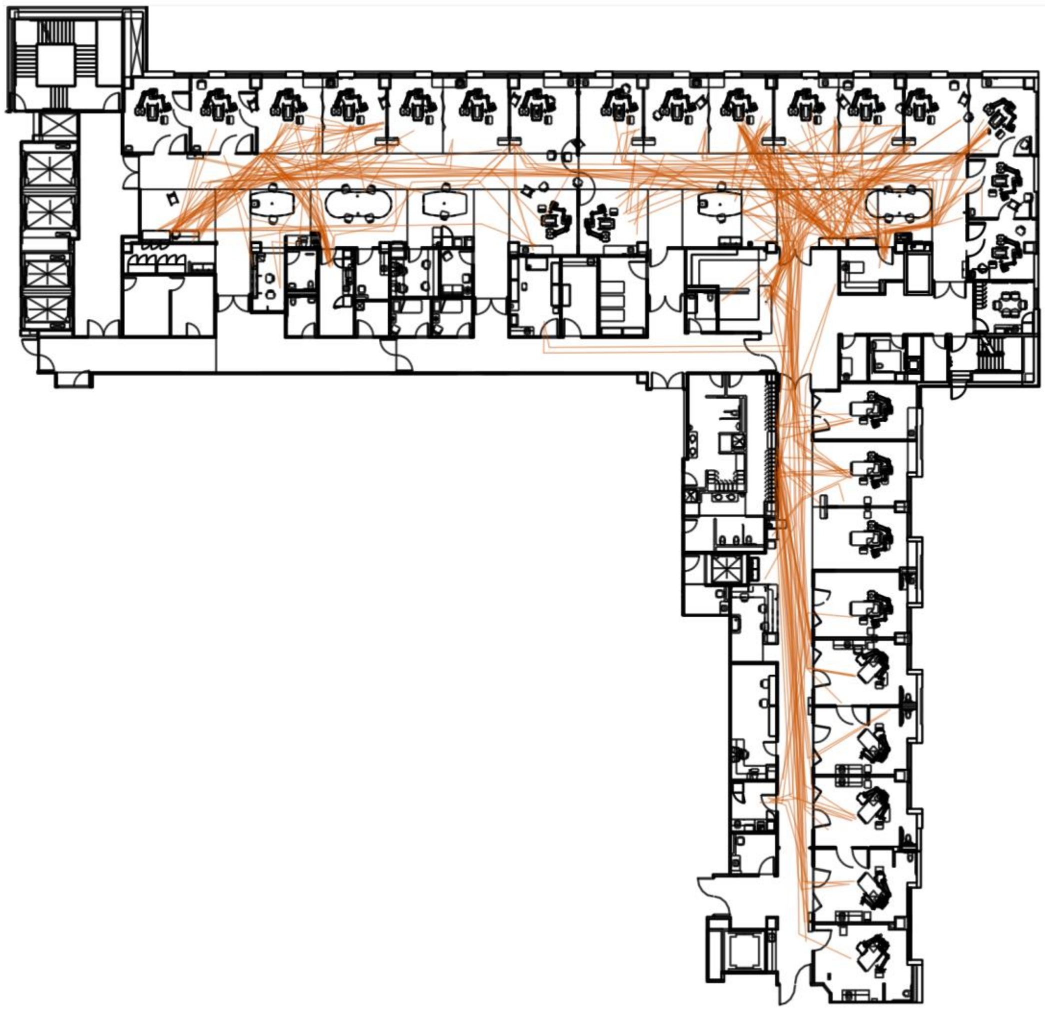


Figure 10 – Bedside nurses' global baths to get supply

3.6 Bedside Nurses' Activities

3.6.1 Bedside Nurses' Time Spent in Different Activity Categories

Table 9 shows the total duration of bedside nurses' time spent at different activity categories for each observation period. The activity categories are broken down to smaller categories in the next table. In average, bedside nurse spent the most time on charting with an average of 188.7 minutes. After charting, the highest-ranking activities were interaction with average 53.6 minutes, care-related activities with 53.5 minutes, handoff with 53.3 minutes, patient assessment with 48.9 minutes, break with 44.2 minutes, medication administration with 36.5 minutes, family engagement with 33.4 minutes, work with care team with 28.7 minutes, feed with 22 minutes, helping other nurses with 14.1 minutes, checking alarms from pump or monitors with 11.9 minutes, and helping with diagnostic procedures (Ultrasound, X-Ray, ECHO, and EKG) with 10.8 minutes. All other activity categories had a duration under 10 minutes on average.

An important implication of these findings is that interactions were common: the second most-frequent category of activity. These interactions included asking or being asked a question, consulting or being consulted with, casual conversations (talking), asking for or being asked help, asking or being asked to watch their patients when they leave the patient bedside, checking in with other bedside nurses or getting checked-in by other nurses. In addition to these interactions, there were task-related interactions such as checking the blood test results with respiratory therapist or care team members (included in blood-related work category), getting a witness for medication or being asked to witness for medication, getting medication signed off or being asked to sign off medication (included in medication administration category) which add up to even more interaction times. There was no significant difference in bedside nurses' time spent in different activity categories between the one and two-patient assignments.

Table 9 - Bedside nurses' time spent in each activity category

Activity Category (group)	Observation 1	2	4	5	6	7	8	9	10	12	13	14	15	16	17	18	19
All care-related activities	26.9	28.7	60.1	14.6	16.4	38.6	93.3	16.5	75.1	44.0	43.4	61.0	56.7	86.9	98.7	39.9	109.3
Blood-related work	17.3	11.4	6.4	19.4	9.8	4.5	7.5	14.2	0.8	10.3	9.1	8.5	1.3	14.9	9.6	14.9	1.8
Break	47.4	40.7	7.2	68.7	39.2	47.9	11.4	47.7	57.7	57.6	40.6	32.4	39.5	36.4	40.4	66.5	69.9
Chart	150.2	223.2	142.6	200.5	162.4	207.2	118.6	255.9	153.3	200.0	211.9	269.6	212.0	152.4	137.8	281.9	129.1
Check alarms	17.1	26.9	17.8	14.7	4.0	5.9	13.1	25.2	14.5	18.4	10.0	4.1	7.9	5.3	4.1	7.3	6.5
Diagnosis	73.6	0.4	3.7		69.2	2.0					21.4		4.3	2.4		2.5	3.6
Drop off items			3.3	4.6	0.4	0.4			2.9				0.8	0.6	0.4		
Electronic communication	7.9	25.6	4.3	1.1	3.5	0.2	9.5		20.5	5.3	18.5	16.7	3.7	6.6	4.4	1.3	1.1
Family Engagement	15.6	10.2	29.4	38.0	53.0	45.9	71.7	27.5	15.3	26.5	63.6	13.0	12.4	34.7	52.5	3.3	54.6
Feed	24.9		33.6	4.2	23.6	46.6	19.2	3.4	28.3	6.5	14.1	71.9	14.2	19.9	41.5	12.1	9.3
Get items	13.2	1.6	23.6	4.5	6.7	8.1	9.0	4.1	8.1	7.1	7.1	0.5	7.4	14.9	10.0	6.4	5.9
Handoff	46.4	24.9	32.1	23.7	52.2	40.6	56.5	44.4	50.2	77.6	50.4	44.0	55.0	99.0	97.3	48.7	63.9
Help other nurses	16.8	5.5	6.9	15.7	21.9	23.1	13.4	6.3	7.8	5.6	17.2	10.3	26.5	8.5	2.8	50.1	1.8
Huddle		9.2	3.7				0.4				2.2	1.9					
Interact	58.7	80.2	51.9	70.4	55.5	52.5	51.3	28.1	84.5	73.4	34.1	89.6	53.0	42.4	22.0	37.8	26.5
Medication	40.0	37.0	78.1	36.9	40.9	19.8	35.0	21.2	41.5	38.2	32.3	12.0	33.6	52.1	30.2	32.4	40.0
Other	2.0	4.7		0.5			0.8		1.0	2.2		1.5	8.6	2.8	3.5	1.6	1.0
Participate in surgery team rounds	1.4	1.6		1.3	0.5	1.8			2.2	2.4	1.3	1.7	1.5	3.4	2.7		0.9
Patient assessment	50.4	43.7	55.3	60.1	62.8	48.2	51.1	77.5	38.6	40.0	51.7	35.4	52.7	45.5	36.6	33.9	48.3
Patient transfer							24.5		30.3						32.9		
Procedure	3.2			7.1		11.9	14.3	17.5	3.1		2.5		23.0	4.8	39.2		19.7
Report to charge nurse	1.1	5.2	0.3	1.7	0.8	2.0		1.2	1.8	1.8	2.6		3.3	1.9	2.7		
Resource nurse drug run		1.1	0.3	0.6				0.4	0.8		0.5			0.2	0.4		0.3
Work with care team	42.7	41.5	48.1	10.8	21.9	18.8	39.9	32.7	23.7	34.2	38.6	11.9	33.7	18.2	18.9	22.9	29.5
Work with resp therapist	29.7	17.0	13.3	13.5	14.6	1.1	0.5	4.9	5.3	0.3	4.5	0.9	0.2	1.3	3.0	0.2	2.7
Work with specialists	3.5	7.7				16.3	4.0					4.5		10.9		1.4	12.8

SUM(Duration in Minutes)

0.2 – 281.9

3.6.2 Bedside Nurses' Activity Counts

Table 10 shows counts of each activity category for different observation episodes. Like activity times, the most frequent activities were charting and interactions with an of average 72.70 and 50.11 times for all observations. After charting and interaction , the most frequently observed activities included patient assessment with an average 34.82 times, medication with 28.64 times, care-related activities with 27.88 times, checking alarms with 17.88 times, feeding patients with 15.0 times, family engagement with 12.70 times, helping other nurses with 11.17 times and getting items with 10.64 times. All other activities had average frequencies below ten times.

Table 10 - Counts of activities in each category

	Observation																
Activity Category (group)	1	2	4	5	6	7	8	9	10	12	13	14	15	16	17	18	19
All care-related activities	9	10	25	4	16	24	31	9	59	36	25	26	32	58	39	21	50
Blood-related work	11	6	6	12	10	1	5	11	1	8	5	4	2	11	5	7	3
Break	4	12	13	16	5	4	4	6	7	10	4	2	4	3	2	7	4
Chart	48	61	77	92	57	77	56	71	59	81	72	61	100	99	73	99	53
Check alarms	14	16	26	10	6	17	12	39	24	30	28	4	18	17	12	19	12
Diagnosis	6	1	3		10	2					10		2	4		3	1
Drop off items			3	4	1	1			3				2	2	1		
Electronic communication	7	6	5	4	5	1	6		10	6	13	5	6	8	3	1	1
Family Engagement	6	1	8	12	23	20	26	10	7	21	17	5	14	12	23	2	9
Feed	21		22	4	15	26	19	5	18	5	6	15	12	29	29	7	8
Get items	11	4	29	8	10	17	13	8	7	9	6	1	9	23	13	7	6
Handoff	4	5	2	2	4	2	5	4	4	4	3	3	2	3	3	2	3
Help other nurses	19	7	1	13	20	9	11	9	7	4	20	13	22	10	3	20	2
Huddle		1	2				1				1	1					
Interact	41	47	62	80	59	53	59	29	44	49	37	35	65	62	41	48	41
Med dropped off		1	1														
Medication	6	23	52	28	25	13	26	9	29	46	25	11	28	50	40	36	40
Other	3	4		1			2		4	5		3	19	3	3	1	1
Participate in surgery team rounds	1	1		1	1	2			1	1	1	1	1	1	1		1
Patient assessment	18	23	30	46	37	42	32	52	29	29	40	19	41	63	36	30	25
Patient transfer							2		8						4		
Procedure	1			1		2	6	4	2		2		4	2	4		3
Report to charge nurse	1	1	1	1	1	1		1	1	1	1		1	1	1		
Resource nurse drug run		1	1	1				1	1		1			1	1		1
Work with care team	12	13	27	4	2	2	11	7	5	10	5	2	3	5	4	3	2
Work with resp therapist	7	10	8	11	15	1	1	4	4	1	8	1	1	3	4	1	4
Work with specialists	2	3				6	2					3		3		3	6

Count of Activity Categ..

1 100

3.7 Bedside Nurses' Interactions

The bedside nurses' total observed interaction times varied between 22 to 89.63 minutes, with an average of 53.6 minutes. The duration of each interaction episode varied between 3 seconds to 32.43 minutes, with an average of one minute and four seconds. The interaction counts for different bedside nurses' observations varied between 29 and 80 times, with an average of 50.1 times per observation episode. No relation was observed between the total interaction time and frequency of interactions across observation episodes.

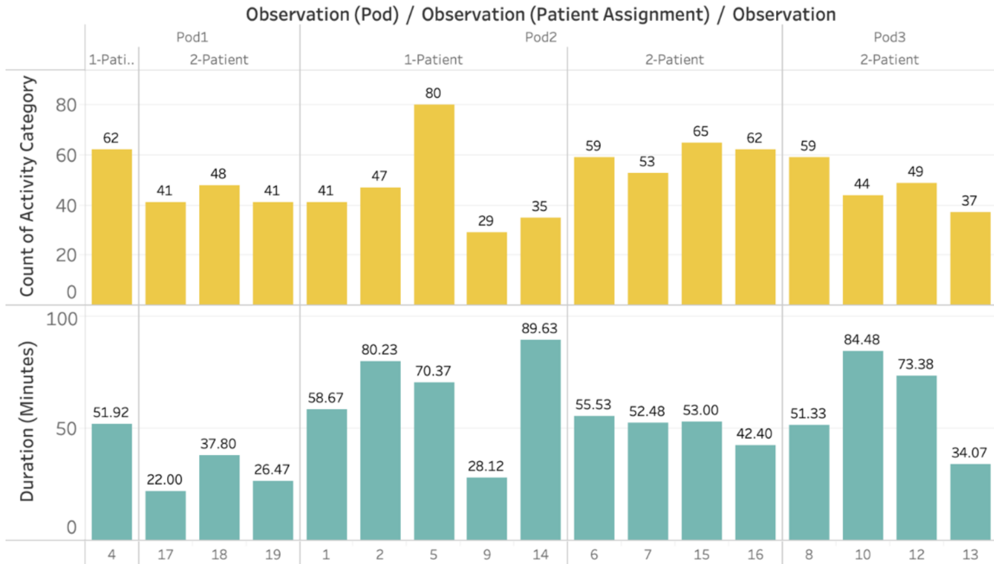


Figure 11 – Total interaction times and frequencies by pods and assignments

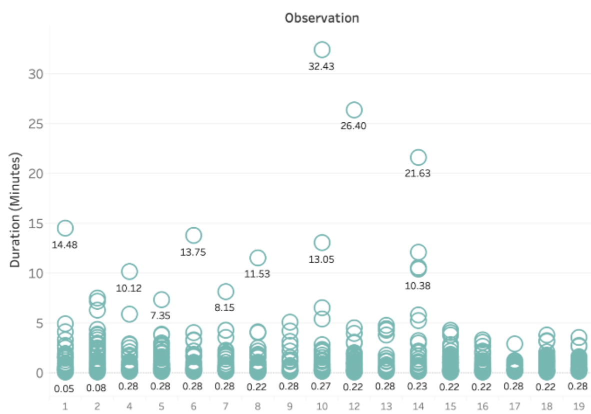


Figure 12- Duration of interactions

There was no significant difference in interaction counts between bedside nurses' interaction counts in the three pods when including both one and two-patient assignments. It partly could be a result of uneven samples for one and two-patient assignments. The observation episodes included six one-patient and eleven two-patient assignment observation. The observation episodes did not include one-patient assignment observations in pod3, and it included only one observation of one-patient assignments in pod1. Another possible explanation is the differences in types of interactions of bedside nurses with one and two-patient assignments. Bedside nurses assigned to only one patient had more planned interactions with other care providers because of the critical situation of their patients.

When comparing all bedside nurses with two-patient assignment, a GML model with a Poisson distribution for interaction counts and a logarithmic link function for pods as the explanatory variable showed a significant difference in interaction counts between the pods. The counts of interactions for bedside nurses in pod2 was significantly higher ($p<0.005$) compared to pod1 and pod3 (Table 11). There was not any significant difference between the frequency of interactions in pod1 and3.

Table 11 – The GML results for comparing bedside nurses' interaction counts with all care providers in pod1, pod2, and pod3

Term	Estimate	Std Error	L-R ChiSquare	Prob>ChiSq	Lower CL	Upper CL
Intercept	3.9007072	0.0459701	2486.5539	<.0001*	3.8091484	3.9893992
Pod[1]	-0.131785	0.0683912	3.8220776	0.0506	-0.268008	0.0003291
Pod[2]	0.189462	0.059228	10.141154	0.0014*	0.0731018	0.3054183

3.7.1 Bedside nurses' Interactions at Care Providers' Work Areas

Three of the central nurse stations (NS1, NS2, and NS3) and the workroom are in pod1. Two of the central nurse stations are in pod2 (NS4 and NS5). The respiratory station is in pod3. By looking at individual observation episodes, it can be observed that most interactions at these central care providers' work areas are from bedside nurses in their adjacent rooms.

Figure 13 – Map of nurse station names

The interaction occurrences at NS1 in pod 1 were from observation 4 and 19 in pod1. The interaction occurrences at NS2 in pod1 included rooms in pod1 (observations 4,17,18 &19) and one observation from pod 2 (observation 7). The interaction occurrences at NS3 in pod 1 were from observation 4 in pod1. The most interaction occurrences at NS4 in pod2 were from observations in pod2 (observations 1,5,6,7,9,15 &16), but they also included observations from pod1 (observation 18) and pod3 (observations 8 & 10). Most interaction occurrences at NS5 in pod2 are from observations in pod2 (Observation 5,6 & 15), in addition to one observation from pod3 (Observation 10). The respiratory station in pod3 had interaction occurrences from both pod2 (observation 6) and 3 (12). The interaction occurrences at workroom in pod1 are from pod1 observations (Observation 17 & 18) and one observation from pod2 (observation 6). Based on these observations, bedside nurses mostly interacted with care providers at their adjacent stations. However, they occasionally visited stations in other pods in order to consult with specific care providers.

Among five nurse stations, the workroom and the respiratory station, the nurse station number 4 (NS4) in pod2 showed higher frequencies of interaction from bedside nurses, as can be seen in Figure 14. The central location of NS4 within the entire unit and its function as the base station for the respiratory therapist in pods can partly explain the higher visit frequencies at this station. This nurse station also had the most occurrence of interactions from coming from beside nurses in other pods (pod1 and 3). The workroom and respiratory station also had interactions from bedside nurses in other pods. The care team and respiratory therapist are based at these locations, and bedside nurses travel from other pods to find them to ask a question or consult. In summary, the centrality of these stations within the layout and attendance of key care team members at these locations are determining in providing interaction opportunities for bedside nurses.

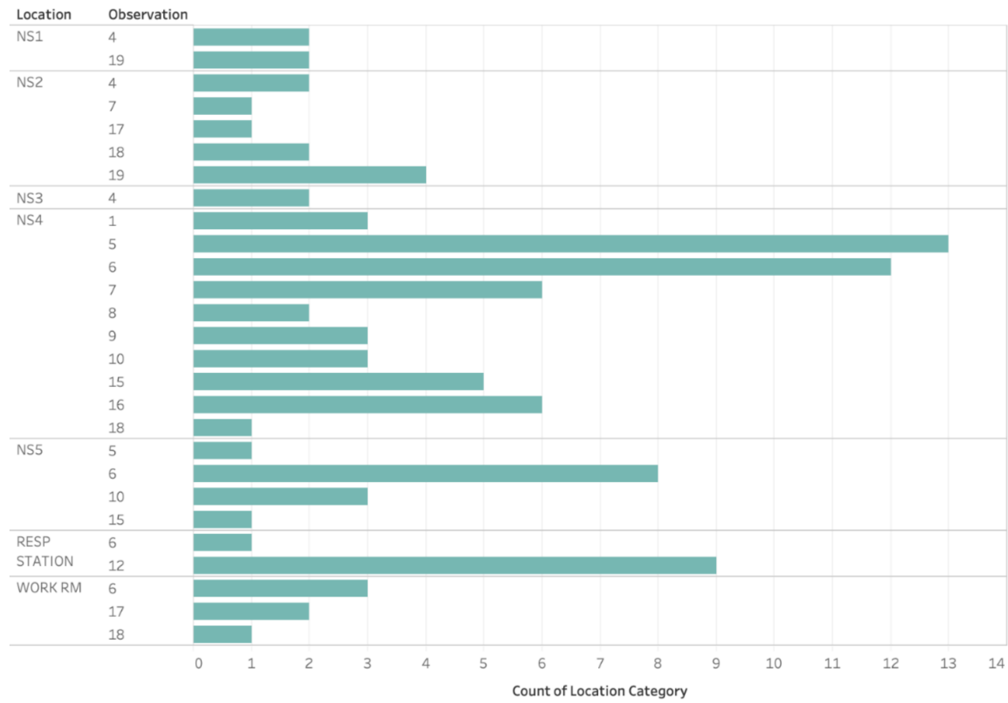


Figure 14 – Count of interactions at different locations

3.7.2 Bedside Nurses' Interactions with Different Care Provider Categories

Figure 15 shows a break-down of bedside nurses' interactions with different care providers. Most bedside nurses' interaction was with their neighbor nurses (40.49%), other bedside nurses (30.40%), care team members including doctors, fellows, advanced practice providers, the pharmacist and surgeons (8.45%) and respiratory therapists (5.40%). Neighbor nurses are defined as the other bedside nurses within 2-room distance from the location of the observed bedside nurse. This distance was equal to 30-32 feet (9-10 meters). The lowest percentage of bedside nurses' interactions was with specialists with 0.23% (ex. occupational therapist, lactation therapist, social worker, physical therapist).

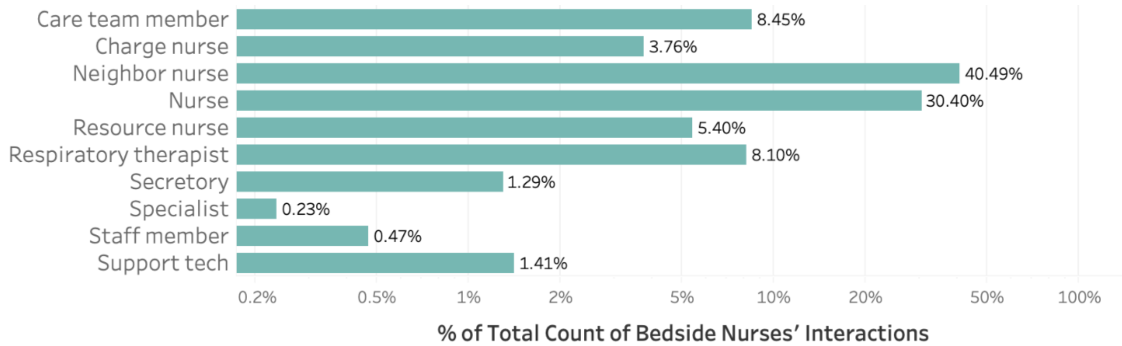


Figure 15 – Bedside nurses' interactions with each care provider category

A GML model with a Poisson distribution for bedside nurses' interaction counts with each category of care providers and a logarithmic link function for pods as the explanatory variable showed a significant difference in interaction counts between the pods. Bedside nurses in pod2 had more frequent interactions with all categories of care providers including other nurses, care team members, resource nurses, and the charge nurse, compared to bedside nurses in pod1 and pod3 (Table 12).

Table 12 - The GML results for comparing bedside nurses' interaction counts with each care provider group in pod1, pod2, and pod3

Care Provider Category	Term	Estimate	Std Error	L-R ChiSquare	Prob>ChiSq	Lower CL	Upper CL
Bedside nurses	Intercept	2.988998	0.0731925	673.76665	<.0001*	2.8416917	3.1288288
	Pod[1]	-0.216409	0.1109125	4.0066004	0.0453*	-0.44025	-0.004404
	Pod[2]	0.278668	0.0923675	9.0475342	0.0026*	0.0974265	0.4600619
Care team members	Intercept	1.1243422	0.1965308	20.21684	<.0001*	0.7023953	1.480873
	Pod[1]	0.0796306	0.2682493	0.0874282	0.7675	-0.467403	0.6025983
	Pod[2]	0.5338859	0.2334467	5.4444791	0.0196*	0.0849117	1.0115813
Resource nurses	Intercept	0.3985349	0.365404	0.9016966	0.3423	-0.588866	0.9823174
	Pod[1]	0.448763	0.4256044	1.2313819	0.2671	-0.333433	1.4946965
	Pod[2]	1.0483841	0.3913156	10.61942	0.0011*	0.3844581	2.0618228
Charge nurse	Intercept	-5.029326	1484.4141	0.3552889	0.5511	-247.7125	0.8323657
	Pod[1]	-12.87206	2968.8282	20.103673	<.0001*	-497.8517	-1.210855
	Pod[2]	6.6387636	1484.4141	16.86473	<.0001*	0.7328709	242.41823
Respiratory therapists	Intercept	0.9310693	0.2024976	15.557284	<.0001*	0.5042498	1.3023198
	Pod[1]	0.455225	0.2622653	2.9065707	0.0882	-0.070364	0.9705016
	Pod[2]	-0.371454	0.2976984	1.6675486	0.1966	-1.002141	0.1853296

Bedside nurses interacted with other bedside nurses and staff mostly for casual seated conversations (talking) by 44.79%, followed by unplanned encounters while walking or others walked by/stopped by 25.93%, asking questions, being asked questions or consulting by 10.42%, asking or being asked to watch patients when they want to leave patient bedside for breaks, using bathroom or other purposes and after coming back for updates by 8.93% and asking help or being asked help by 8.44%.

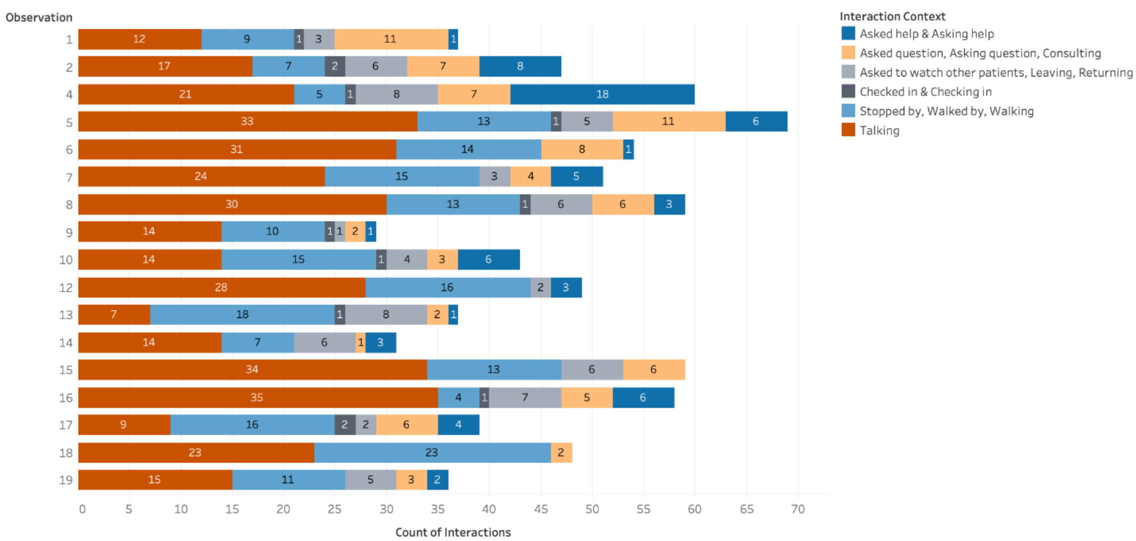


Figure 16 – Bedside nurses' interactions for different contexts for each observation episodes

Most bedside nurses' interactions happened when bedside nurses were at their assigned decentralized nurse stations by 44.91% and assigned patient rooms by 21.86%, followed by unassigned patient rooms and unassigned centralized nurse stations by 9.43% and 8.56%.

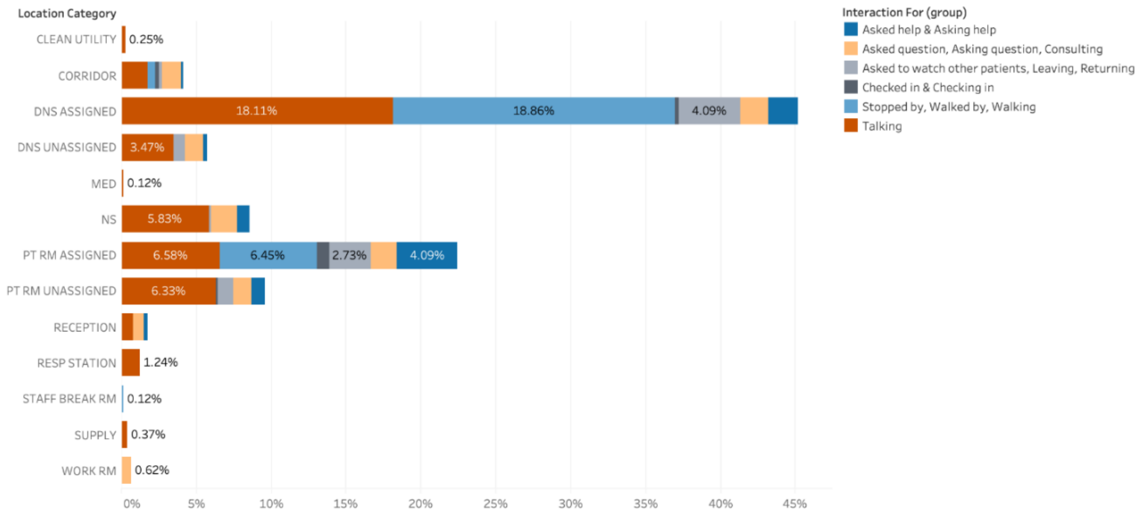


Figure 17 – Percentage of total interaction counts at each location category

These findings show that bedside nurses mostly did not leave their assigned patient bedsides or decentralized nurse stations for interactions. They engaged in conversations with other nurses and care providers who were adjacent to them (close enough and in their line of sight) or walked/stopped by while at these assigned locations. If they had a question, needed consult, needed help, or needed to find a nurse to watch over their patient while they were gone, they first checked the adjacent areas while they were in their assigned locations. If they did not find anyone, they then would go to adjacent patient rooms, nurse stations, or decentralized nurse stations for these purposes.

Figure 18 shows the distribution of different interaction contexts across different locations for bedside nurses. This chart helps understand why bedside nurses interacted at these locations. Based on this figure, 100% of interactions of bedside nurses at the workroom in pod1 was to ask questions or consult with the care team members at this location. Also, 100% of their interactions included casual conversations with other bedside nurses and care providers while they were at clean utility rooms, Pyxis medication stations, supply closest, or the respiratory station for task-related purposes. Bedside nurses traveled to other decentralized nurse stations and patient rooms to engage in casual conversions with other nurses 64.23% of the times, for asking questions and consulting 16.26 % of the times, to ask them to watch over their patients 11.38% of the times and to ask help 7.32% of the times. Bedside nurses went to centralized nurse stations to engage in casual conversations 68.12% of the times, to ask a question or consult 20.29% of the times, and to ask help 10.14% of the times. In the corridors, 42.42% of bedside nurses' interactions included casual conversations, while 30.30% for asking questions or consults.

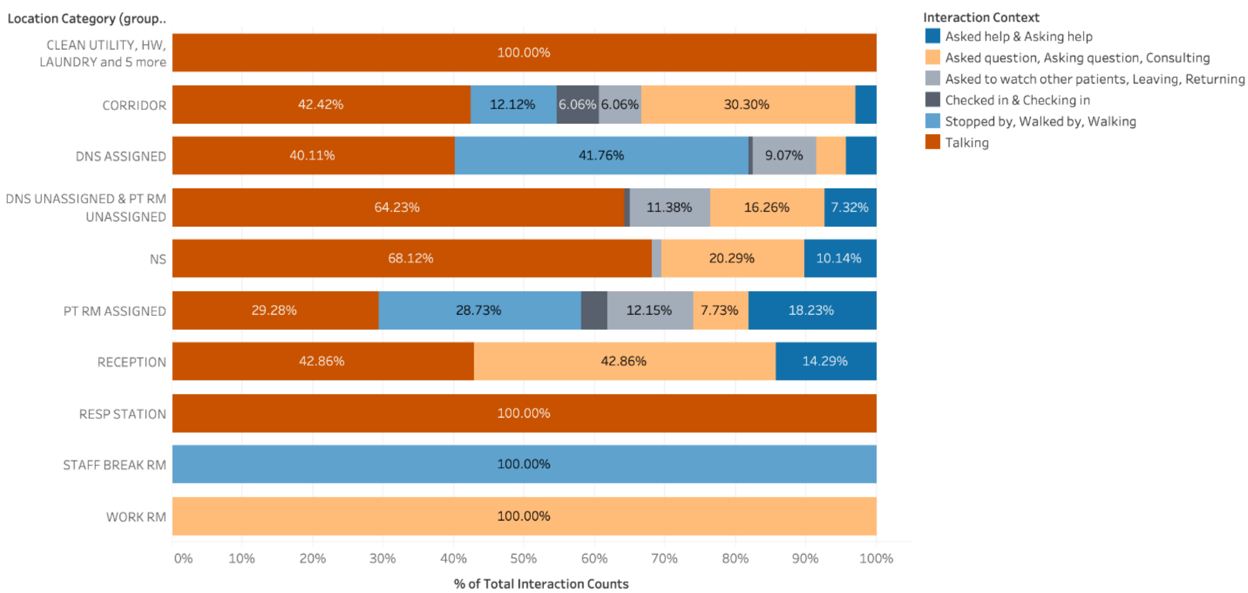


Figure 18 – Bedside nurses' interaction context categorized by location categories

3.8 Other Care Providers' Activity Locations

This study has mainly focused on bedside nurses' activities and workflow. Activity data on other care providers, including a respiratory therapist, two resource nurses, an attending doctor, and a nurse practitioner, was also collected to understand the dynamics of activities between them and bedside nurses. The analysis of collected data shows that these group of care providers mostly spent time at centralized nurse stations in pod1 and pod2 when they were not engaged in patient care activities. Care team members (the attending doctor and the nurse practitioners) did not spent much time in their assigned workroom.

Figure 19 - Care providers' locations at idle times

The respiratory therapist spent the most time at assigned patient rooms (40.3%) and nurse stations (38.6%). The Attending doctor and nurse practitioner spent the most at assigned patient rooms (57.41%), followed by unassigned patient rooms (16.49%) and nurse stations (15.45%). The resource nurses spent their most time at patient rooms (44.19%), decentralized nurse stations (17.89%), and nurse stations (10.02%).

Of all the nurse stations and assigned areas to these care providers, the nurse station number 4 (NS4) in pod2 had the highest frequency of visits, followed by nurse stations 2, 3 and 5. The NS4 in pod2 has a central location in the unit. It is usually used by the charge nurse, the respiratory therapist assigned to pod2 and the resources nurses and is frequently visited by care team members who want to interact with them. The centrality and usage of this nurse station make it the most frequently visited workstation within the unit by care providers.

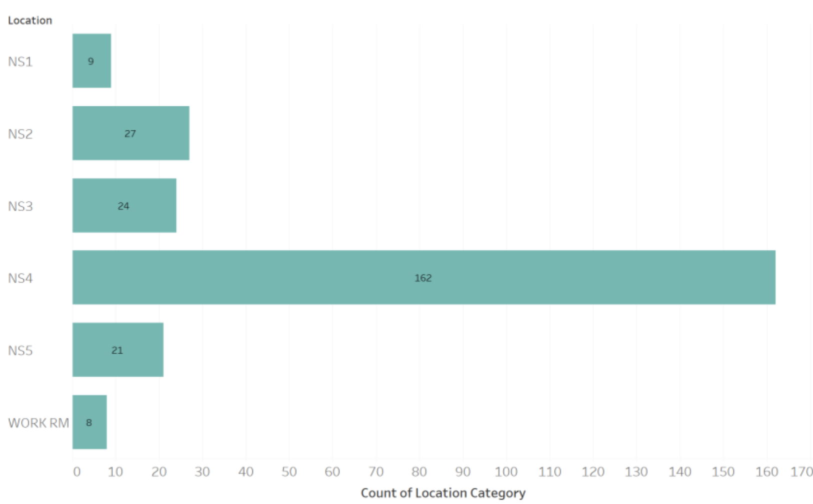


Figure 20- Care providers' use of workstations

3.9 Findings from the Field Study

The observational data was analyzed to understand how care providers spent their time at different locations within the CICU. Although this study collected data on all care providers, it mainly focuses on the analysis of data recorded for bedside nurses. The results of the analysis showed that bedside nurses spent 82% of their time at assigned patient rooms or decentralized nurse stations and 18% at other location. They left their assigned areas for getting medication, nutrition, supply or equipment for patient care activities, taking breaks, getting help, or consulting for patient care. Bedside nurses' movements for different activities happened both in local (within their assigned pod) and global scales (between all pods). They mostly moved locally for medication and nutrition delivery but moved globally for gathering supply and equipment, taking breaks, or consulting with care team members.

Bedside nurses spent most of their time on charting and interactions (planned and unplanned), followed by patient care activities. A significant finding of this study is the occurrence of interactions as the second most observed activity among bedside nurses, after charting. Bedside nurses mostly interacted with their neighbor bedside nurses within a two-room radius (40%) and other bedside nurses everywhere else (30%). A comparison of occurrence of the interactions between the three pods showed that bedside nurses in pod2 had higher records of interactions compared to bedside nurses in pod1 and pod3. Pod2 in the CICU has a higher density of rooms (higher compactness) compared to pod1 and pod3. It is centrally located and connects pod1 and pod3 together. The central location of pod2 between the two other pods makes it a transition space between the two other pods where a higher number of movement paths pass through (higher betweenness).

CHAPTER 4. MODELING AND SIMULATION

This chapter presents a summary of the simulation modeling techniques used in the current study. It describes the specifications of the simulation environment and agents' profiles. The modeling strategies for simulating different types of agents' activities are described in this chapter, including using Markov chains process modeling approach to simulate bedside agents' unstructured activities. This chapter continues by describing how model logs have been analyzed for model validation and verification. Lastly, the spatial analytic methods integrated into the simulation model for measuring care providers' encounter episodes are explained.

4.1 Simulation Model

This research study uses simulation modeling for studying spatiotemporal experience of care providers. The simulation model is expected to reflect the layout, the agents representing care providers with their assigned attributes and logics, as well as their workflow and activities to generate agent movements in the simulation environment. As a product of agents' movement, the model then tracks and records agents' encounter measures at defined time steps to understand the spatiotemporal experience of agents based on their assigned locations. The figure below demonstrates the conceptual framework of the proposed simulation model.

This study employs Anylogic software to build the simulation model. It uses a multimethod modeling approach by integrating agent-based simulation (ABS) and discrete event simulation (DES). Agents are defined using the Pedestrian Library to simulate agents' flow in the physical environment. By defining agents as pedestrians, they can move in continuous space and react to physical obstacles such as walls, other agents, and space markups. Pedestrian agents move in the defined physical environments according to defined behavioral and movement rules. The agent movements can be determined through process modeling flowcharts and states.

In order to build a simulation model with an agent-based approach to represent the providers' behavior ad movements in the CICU, the agents' environment, the agents' properties, as well as their interaction with the environment and other agents needed to be defined (Friesen & McLeod, 2014).

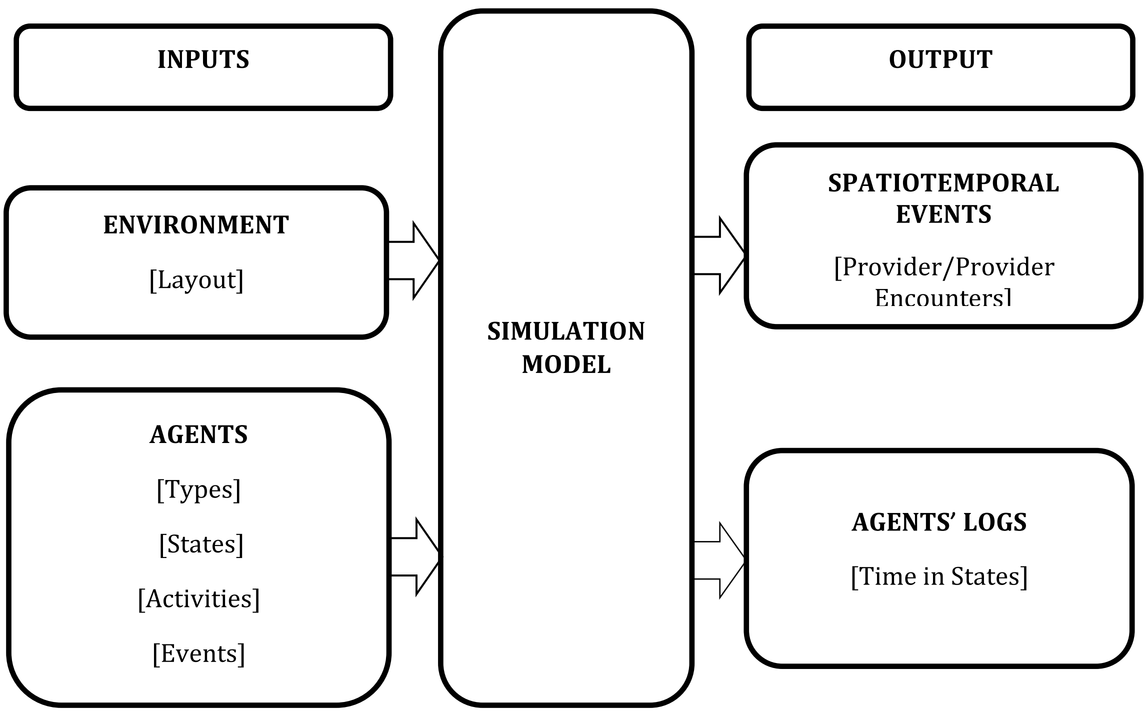


Figure 21 – The conceptual framework of the simulation model

4.2 Modeling Simulation Environment

The model environment is the CICU layout, where all the activities and processes happen. The environment includes certain spatial information such as physical barriers (walls and floor cases) and activity zones. Walls and other physical barriers can influence agents' movements through obstacle avoidance logics as agents navigate through space while avoiding obstacles. The space markups have been used to define activity areas such as patient bed areas, nurses' work areas, and other key locations.

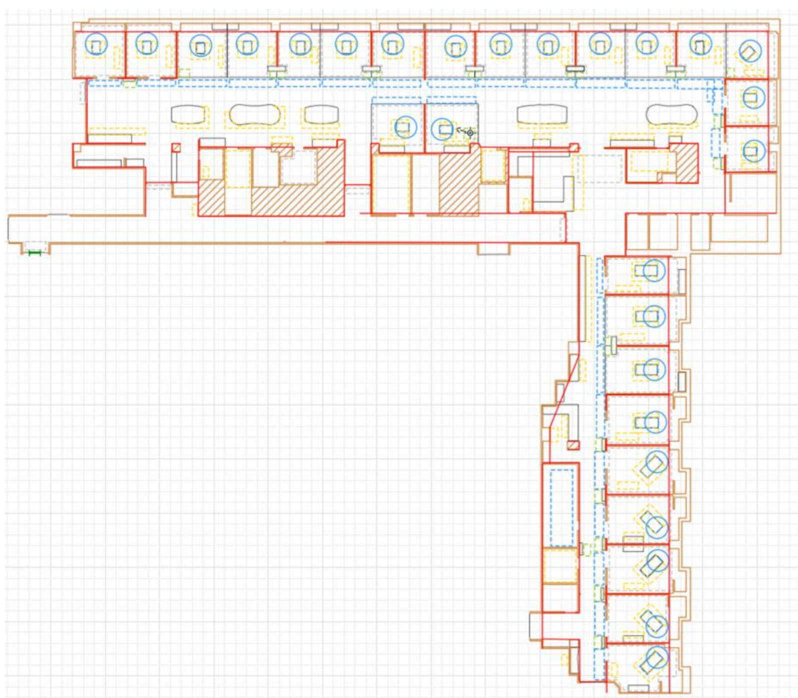


Figure 22 – Setting up the layout for simulation environment

4.3 Modeling Agents

A set of agents were defined in the simulation model including, thirteen agents representing bedside nurses, two agents representing resource nurses, four agents representing care team members (two attending doctors and two nurse practitioners), three agents representing the respiratory therapists, and an agent representing the charge nurse. Although the CICU involved more care providers, the selected population is the representative of entities that are always working on the unit.

Since this study focuses on care providers' activities and movements, patients' characteristics are modeled as part of the bedside nurses' profile and are embedded in bedside agents' decision-making processes. Patients' characteristics such as medication, nutrition, required diagnostic and regular procedures, admission and discharge, and all other determining attributes are all defined as events and parameters within bedside nurses' agents, which changes in workflow and decision-making processes based on patients' condition.

The collected observational data has been used to inform agents' modeling including agent's movement strategies (local and global), spatial occupancy for different activities, implementing spatial logics in agent's conditional activities, defining logics of planned interactions with other care provider agents, and defining unique behavior logics for individual agents.

4.3.1 Agent profiles

A set of parameters was assigned to each agent for characterizing specific agent properties. These parameters include basic agent properties, such as the number of assigned patient rooms, and time-related parameters, such as agent schedules, arrival time, duration of different activities. The time data used in the simulation were collected through site observations, and time distributions were identified based on the collected data.

The agents' parameters also include location-related parameter where agents assigned patient rooms, assigned work areas, assigned nurse stations, or other base locations related to the agent are defined. The value of each location parameters is assigned through space markups in the simulation model. The location parameters were used to assign agent locations or destinations in different activities within the model environment. Instead of using fixed location parameters, the location of agents is assigned trough parameterized locations that can be changed for testing different layout options. Table 13 shows the location parameter assigned to agents.

Table 13 – Agents' assigned location parameter

Agent Name	Assigned Location	Agent Name	Assigned Patient Rooms
Bedside Nurse 1	Patient Rm 2109	Resp. Therapist 1	NS2
Bedside Nurse 2	Patient Rm 2110	Resp. Therapist 2	NS4
Bedside Nurse 3	Patient Rm 2104-2105	Resp. Therapist 3	Resp. Station
Bedside Nurse 4	Patient Rm 2101-2102	Resource Nurse 1	NS4
Bedside Nurse 5	Patient Rm 2103	Resource Nurse 2	NS5
Bedside Nurse 6	Patient Rm 2107-2108	Charge Nurse	NS4
Bedside Nurse 7	Patient Rm 2112-2113	Attending Doctor1	NA
Bedside Nurse 8	Patient Rm 2115-2117	Attending Doctor 2	NA
Bedside Nurse 9	Patient Rm 2114-2116	Nurse Practitioner 1	NA
Bedside Nurse 11	Patient Rm 2119-2120	Nurse Practitioner 2	NA
Bedside Nurse 12	Patient Rm 2122-2123		
Bedside Nurse 13	Patient Rm 21124-2125		
Bedside Nurse 14	Patient Rm 2126-2117		

Other parameters included agents' speed. Since the observational data did not provide enough information to calculate care providers' speed in different activities, the average walking speed of 1.1-1.5 meter per second for normal, healthy individuals was assigned to agents (Nadeau, Betschart, & Bethoux, 2013; Shiavi, Bugle, & Limbird, 1987).

4.3.2 *Agent States*

When agents initiate an activity, they enter a state. The transition between different activities happens through transitions between states. The transition between different states can be triggered as a result of the occurrence of different types of events. The event trigger can be defined as a timeout event (after a specified time), rate (based on time intervals), condition (once a condition becomes true), or message (upon receiving a message). The message trigger can be sent to an agent by itself or from other agents and allows for communication between agents. For example, when the care team arrives at the patient room, a message from the attending doctor will be sent to the bedside nurse to move towards the attending doctor and participate in the rounds.

The diagram below shows parts of a state diagram defined for a bedside nurse agent. Based on the observational data, charting was the most frequently observed data for bedside nurses. Therefore, the "charting" state would be considered as the origin state for bedside nurse agents and they get transferred to other states, and activities from the charting state.

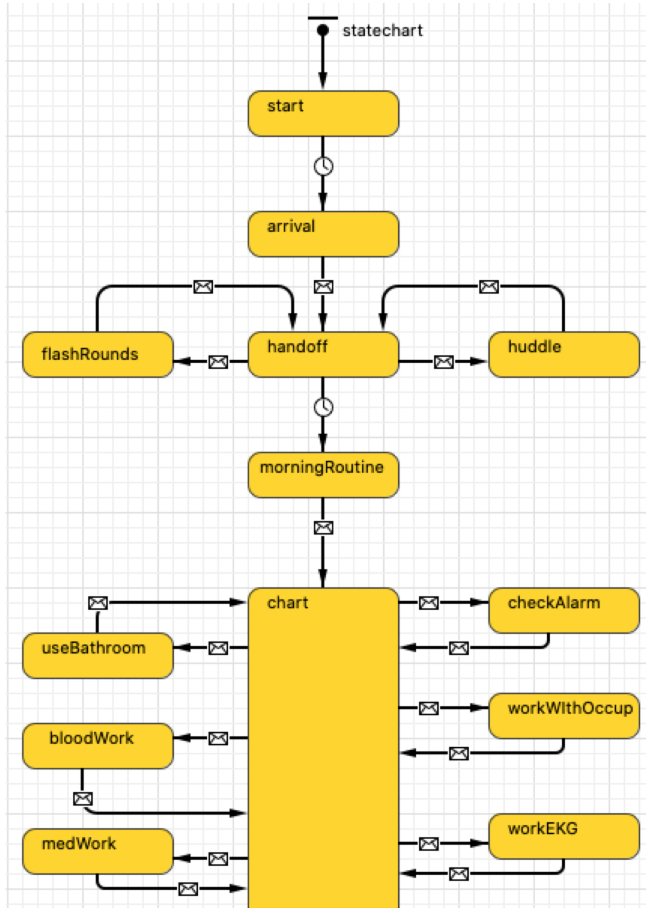


Figure 23 – Example of an agent state chart

4.4 Processes and workflows: Structured and Unstructured Activities

Process are sequences of activities performed by agents for completion of patient care activities, non-care related activities, or personal needs. Checking patient vitals, medication administration, nutrition delivery, participating in morning rounds, or taking a lunch break are some example of these processes which include specific activities in specific spatial zones. Agent workflows and processes can be initiated based on defined schedules (certain time during the day), based on rates (n time times a day) or based on certain events (such as alarms or emergency patient events). This data was collected through site observations and was used to build agents' movement and workflow logic.

Based on the collected data on the care providers' activities, two distinct sets of activities were identified. The first set of activities are structured activities with distinct process flows where the person goes through a defined set of steps to accomplish a task. Although the process flow might have variations, the main structure of activities remains the same. Examples of these activities include medication delivery, nutrition delivery, or taking a break.

The structured activities can be initiated based on defined schedules such as handoffs, morning surgery flash rounds, care teams' morning and afternoon rounds, respiratory therapist morning, noon and afternoon rounds, and care providers' lunch breaks. Although there are slight variations in the timing of these activities, they are scheduled to happen at certain times of the day. The structured activities can also be initiated based on patient needs and care providers' preferences but include a predictable sequence of multiple steps. Medication administration, nutrition delivery, and blood works are some examples of this category.

The second set of activities are unstructured activities that do not contain a clear process flow, schedule, or steps and happens in a stochastic manner. Patient assessment, cleaning work areas, getting supplies, or helping other nurses are examples of such activities. In upcoming sections, a detailed description of these activities and their implantations in the simulation model will be described.

Every time that an agent transitions to a new state, they enter a new set of activities through a process that is defined by discrete steps and workflow logic. The process can be as simple as going from one location to another or be more complicated by adding delays and output selections. The below process flow shows an example of a blood work process for a bedside nurse, including getting required supplies, blood analyzer, drawing blood, testing blood, dropping off the blood, and consulting the blood sample result with a care team member or respiratory therapist.

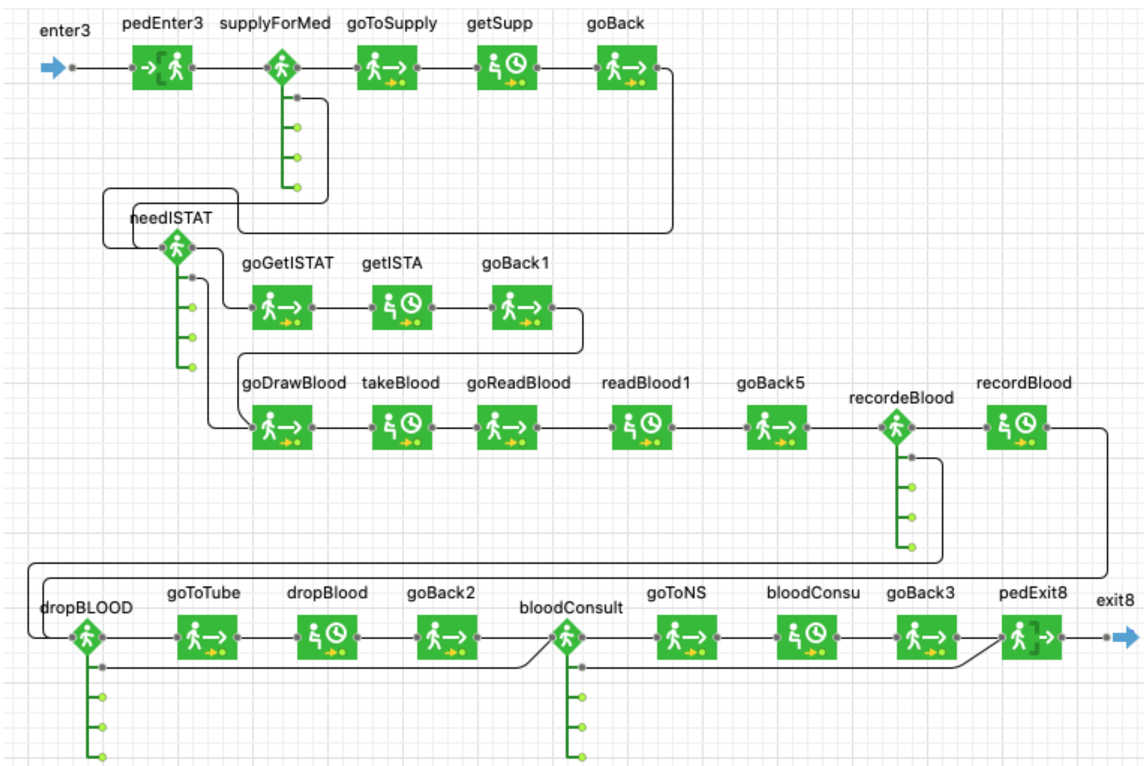


Figure 24 – Example of a process flow modeled for a bedside agent

4.5 Modeling Care Providers' Workflow and Activities

The first step in building the simulation model is to understand the workflow and sequence of activities. For CICU patients, the workflow is straightforward: they arrive in CICU; they stay in the CICU for a specific duration, and then they get discharged. For care providers, the workflow is more complicated and includes direct patient care activities (including direct care, patient assessment, medication administration and dealing with emergency situations) non-care, task-related activities (including cleaning and re-stocking medication and equipment and attending care coordination rounds) and personal activities (breaks).

A workflow is a group of tasks which are chronologically grouped into processes with a set of required resource to accomplish specific goals (Cain & Haque, 2008). Understanding nurses' workflow has been a critical factor in improving the efficiency of care, resource planning, process improvement, and creating value-added care. Most studies about nurses' workflow only have looked at the time spent in different activities. Although this information is valuable, it does not provide useful insights toward understanding the sequence of activities in nurses' workflow. Nurses continuously switch between different tasks caused by unexpected and urgent events. These deviations from the initial process steps make it difficult to look beyond variations and understand the existing workflows.

A study of nurses' workflow on two medical-surgical units concluded that there were too many deviations from activities to be able to come up with any workflow sequences or patterns and suggested that more complicated analytical tools such as conditional probabilities and Markov chains are needed to identify the intricate patterns

(Cornell et al., 2010). Another study found distinct sequences in nurses' activities in a medical-surgical unit for patient round assessments, medication delivery, call response, nourishment delivery, supply delivery, and break (Nanda et al., 2015). Nanda et al study argued that nurses walking distances depends on the sequence of activities and frequency of visiting different locations. The most frequently visited locations in this study were patient rooms, assigned nurse stations, clean supply, and medication rooms. Although this study presented an example of the medication delivery process, steps and possible deviations, it did not report a comprehensive analysis of nurses' workflow.

The current study argues that it is possible to model and simulate the ongoing activities in each setting by recognizing two categories of activities: structured and unstructured. The process steps of structured activities and their associated workflows, along with the existing variations and deviations, can be identified through a detailed analysis of the observational data. For unstructured activities with a stochastic nature, transitions between different activities and locations can be modeled through a Markov Chain process by modeling state transitions based on probabilistic rules.

4.6 Modeling Structured Activities

In the first encounter with the CICU environment, one might observe a complex system that exhibit a chaotic environment with all the rooms, patients, and care providers. However, with a closer look into the collected data, it appears that there is not much randomness and irregularity in movements and occupancy patterns after all. The critical nature of patients in the pediatric cardiac intensive care environment calls for close observation. Therefore, all movement in the CICU environment is to fulfill a task or perform the required functions.

The most structured body of activities belongs to bedside nurses whose primary responsibility is direct patient care. The respiratory therapists and care teams have certain scheduled activities during most of their shifts and spend the rest of their time responding to checking patients based on their situation and upcoming events. The activities of resource nurses have the highest level of unpredictability and randomness. Resource nurses are responsible for assisting bedside nurses based on their demands and needs at each specific time, which does not follow any patterns.

For every agent in the simulation model, all structured activities are modeled through process mapping with considering existing variances and conditional occurrences. In the next section, the main categories of structured activities for bedside nurses are explained.

4.6.1 Bedside Nurses' Structured Activities

Starting off the Morning Shift: The morning shifts for all the observed bedside nurses started with handing off with the nurse from the previous shift. Most bedside nurses were also able to participate in the morning nurse huddles during or after handoffs. They also participate in the morning surgery flash rounds, which happens around the same time, depending on when the team arrived at their assigned patient rooms. After handoffs, a few steps, such as cleaning the working surfaces, checking the patient chart, patient assessment, and checking patients' vital signs, were followed, with no specific sequence. After almost an hour, they participate in the morning care team and respiratory rounds depending on when these rounds arrive at their assigned rooms. The morning handoff process could start as early as 6:29 am and ends as late as 7:40 am.

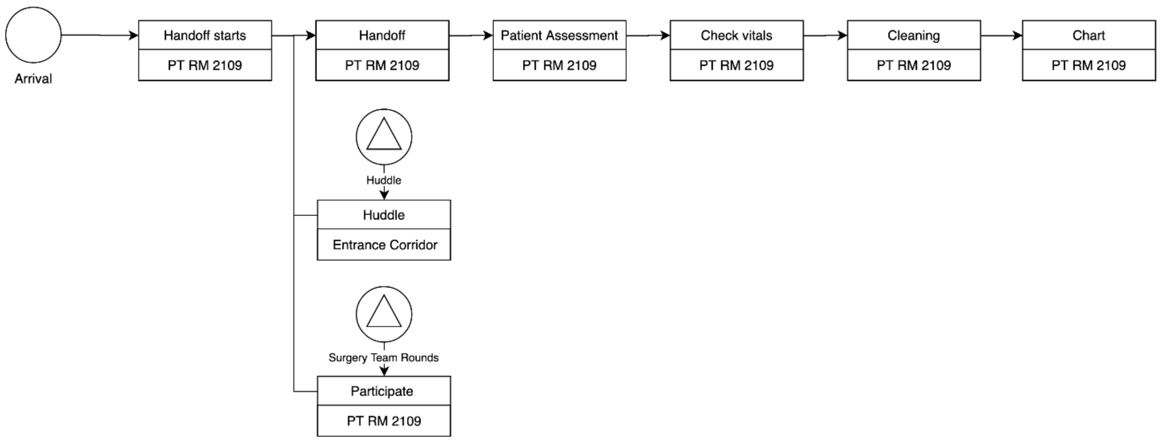


Figure 25 – Example of morning routine for a bedside nurse

<u>Medication Administration:</u> The medications can be delivered to patient beds in 3 different ways: it can be dropped off by the pharmacist, delivered through the tube system at a pneumatic tube station, or can be picked up from one the Pyxis medication stations in the pods by bedside nurses. Antibiotics and blood pressure medicine are usually delivered to the patient bedside by the pharmacist. Bedside nurses can get pain medication, fluid tubes, flushes, and other types of drugs from the Pyxis medication station in each pod. Bedside nurses also pick up the incoming patient medications from pneumatic tube stations for their patients. Sometimes other nurses or care providers hear the incoming medication alarm and bring their medications to them.

If the bedside nurses want to get pain or sedative medications from the Pyxis medications, they need to get another nurse to witness for their medication at the Pyxis station to ensure the accuracy of the medication and its dosage. They usually call for a witness and a nearby nurse who sees or hears them witness for them. In pod3, it usually becomes difficult because of the low visual exposure to the med stations from other nurse stations. After getting the witness, they get the medication, take it to their charting station at the patient room, and scan the medication into the medical records. For certain medications such as sedative and pain medication, they need to get the dosage signed off (confirmed) by another nurse. To get the medication signed off, they usually ask one of the nurses in their neighbor patient rooms to come over and sign off the medication for them. Alternatively, they went to the neighbor stations and asked them to sign off the medication for them. Finally, they prepare the medication and give it to their patient by mouth, injection, or IVs.

There are slight variations in the sequence of activities for medication administration. For example, a nurse might prepare the medication and then scan it, or have it signed off. Also, they might administer a few different types of medication together. They might get the medication and scan it, perform other tasks or get interrupted by other ongoing procedures, and then prepare and administer the medication.

If the administration of medications is through infusion, an alarm sound from the infusion pump gets released after the completion of the infusion to notify the bedside nurse. The infusion time varies for different medications between 5 to 30 minutes. After hearing the alarm, the nurses get flush tubes from the Pyxis stations and flush water after medications to wash off the remaining med from the containing line. For this study, getting the flush tubes and flushing water after the medication was also included in the medication administration category.

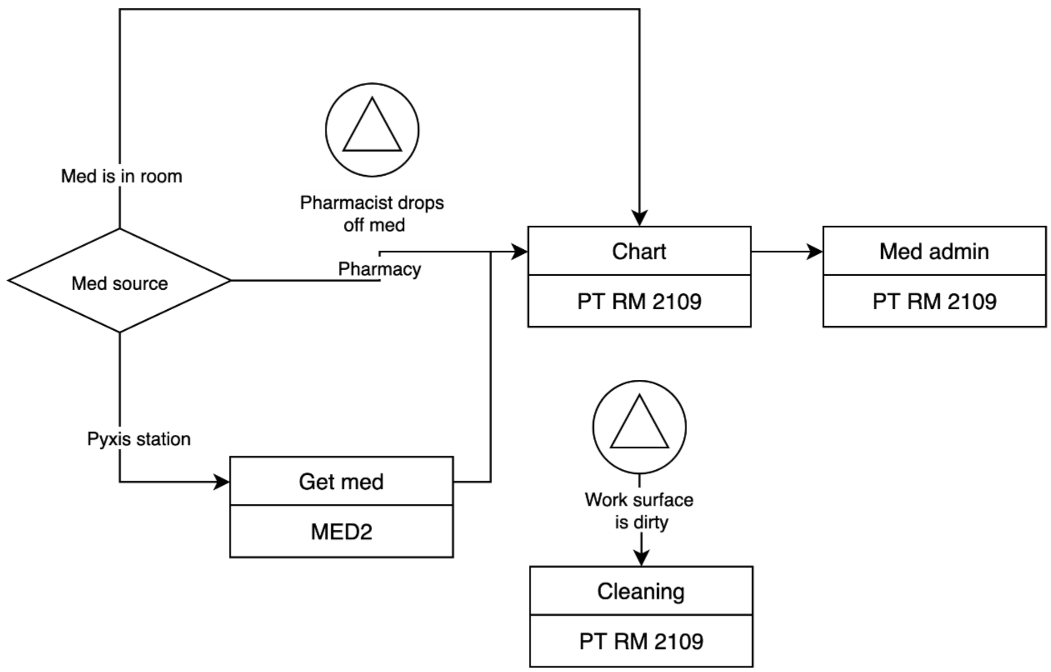


Figure 26 – Example of medication delivery process for a bedside nurse

<u>Blood work:</u> Bedside nurses are responsible for taking blood samples from patients. After drawing the blood, they test the sample using i-STAT blood analyzer machines, which operate with single-used i-STAT test cartridges. For patient-side blood test with i-STAT, nurses insert 2-3 drops of the blood sample into the cartridge. After that, they will be able to read the test results in 2-3 minutes. The i-STAT machines can be found at patient rooms, decentralized charting stations, and centralized nurse stations. If bedside nurses do not have the i-stat machines in their assigned patient rooms or charting station, they take a trip to find a machine from other charting stations or nurse stations.

The blood test is usually done to check patients' blood gas levels or cortisol levels after administering certain medications (usually 30 minutes after medication administration). If the patients are in stable conditions, the blood test happens every 8 hours. For critically ill patients, it happens every 4 hours. After testing the blood sample, bedside nurses might consult the results with respiratory therapists or care team members to update them on the status of patients and take necessary actions if necessary. They might also drop off the blood sample at one of the pneumatic tube stations to be transferred to the laboratories for further testing. After blood samples get delivered to the labs, nurses get notifications through their charts. If they do not receive any notification, they check the pneumatic tube stations to make sure that the blood sample has gone through the system.

The sequence of blood draw activities includes drawing a blood sample, getting the i-STAT machine if not in the room, testing the blood sample, reading the blood test results, charting the result into the charting system, checking the results with respiratory therapists or care teams and dropping off the sample at the pneumatic tube stations. There are slight variations in the sequence and occurrence of these steps depending on other ongoing processes, location of the i-stat machine, and availability of care team member to check the results and need for further testing the sample.

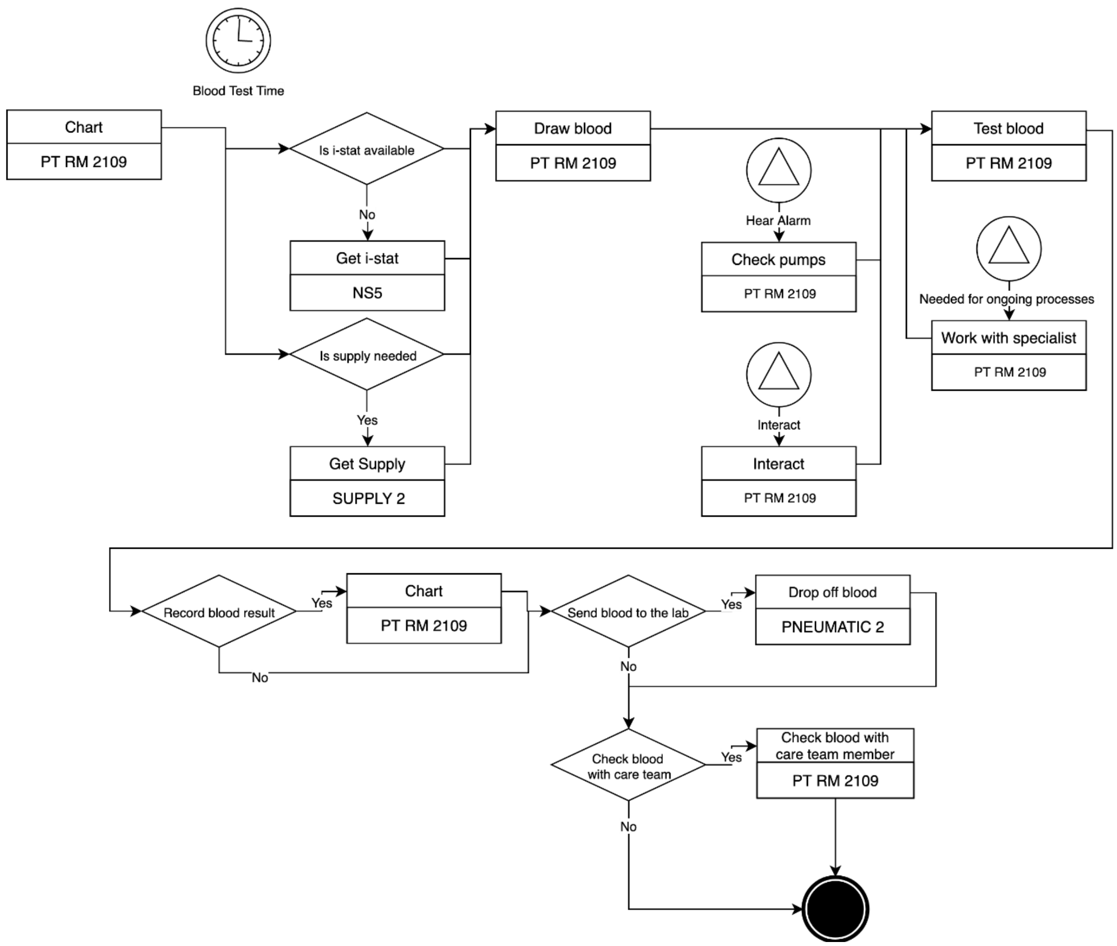


Figure 27 – Example of blood work process for a bedside nurse

<u>Nutrition delivery:</u> The process of feeding patients depends on specific patient conditions. If patients are sedated, they usually get their nutrition through IV bags, which does not require bedside nurses to get and prepare food for them. If patients feed on breast milk, it usually gets delivered to patients through milk tubes and pumps for younger patients. If patients are in good condition, sometimes bedside nurses try to give milk to them through milk bottles. Patients might get food through food bags. If patients are older

and can eat, the bedside nurses order food from the hospital kitchen and help them eat the food once it gets delivered to the bedside.

For patients on breast milk, mothers of newborn babies drop off breast milk bottles when they visit their patients. Bedside nurses label the breast milk bottles with patient's name and date, pack, and store them in the clean utility room for future use. The formulas and packaged milk are also kept in the clean utility rooms. During the day, bedside nurses pick up the formula or breast milk from one of the clean utility rooms, scan them into the charting system, prepare it at the bedside and feed it to patients. This process might have slight variations based on other ongoing activities, milk types, and availability of required supplies.

If the patient is on breast milk, bedside nurses need to unfreeze the milk before preparing it and putting it in the milk tube. For that, they should grab a milk warmer cabinet, which can be found in the corridors, nurse stations, or other patient rooms. After unfreezing the breast milk, they prepare it and put it in a pump that delivers it to patient. For patients on formulas, they usually grab the milk from one of the clean utility rooms, get water and mixing cups from one of the supply closets and clean utility rooms, mix the formula (with water or milk) and feed it to patients through milk tubes. During the feeding process, sometimes bedside nurses grab labels for milk tubes from nurse stations to label the tubes. After feeding the patient, they return the unused milk to the clean utility rooms to store there.

Usually, 15 minutes after putting the milk tubes in, an alarm sound goes off to indicate the completion of delivery. Upon hearing that alarm, the bedside nurse flushes water after the milk to wash it off from the remaining milk. About 3 minutes later, another alarm announces the completion of the flushing. If a baby is not receiving milk through breastfeeding or bottles, the bedside nurse swab inside their mouth with a small amount of breast milk for mouth care to introduce baby to the taste and smell of milk.

Bedside nurses usually inform a neighbor nurse to watch their patients before leaving the patients' bedside to get milk from the clean utility rooms, especially if their assigned patient is far from the clean utility room. After returning from the clean utility room, the neighbor nurse will update them if any events happened while they were gone.

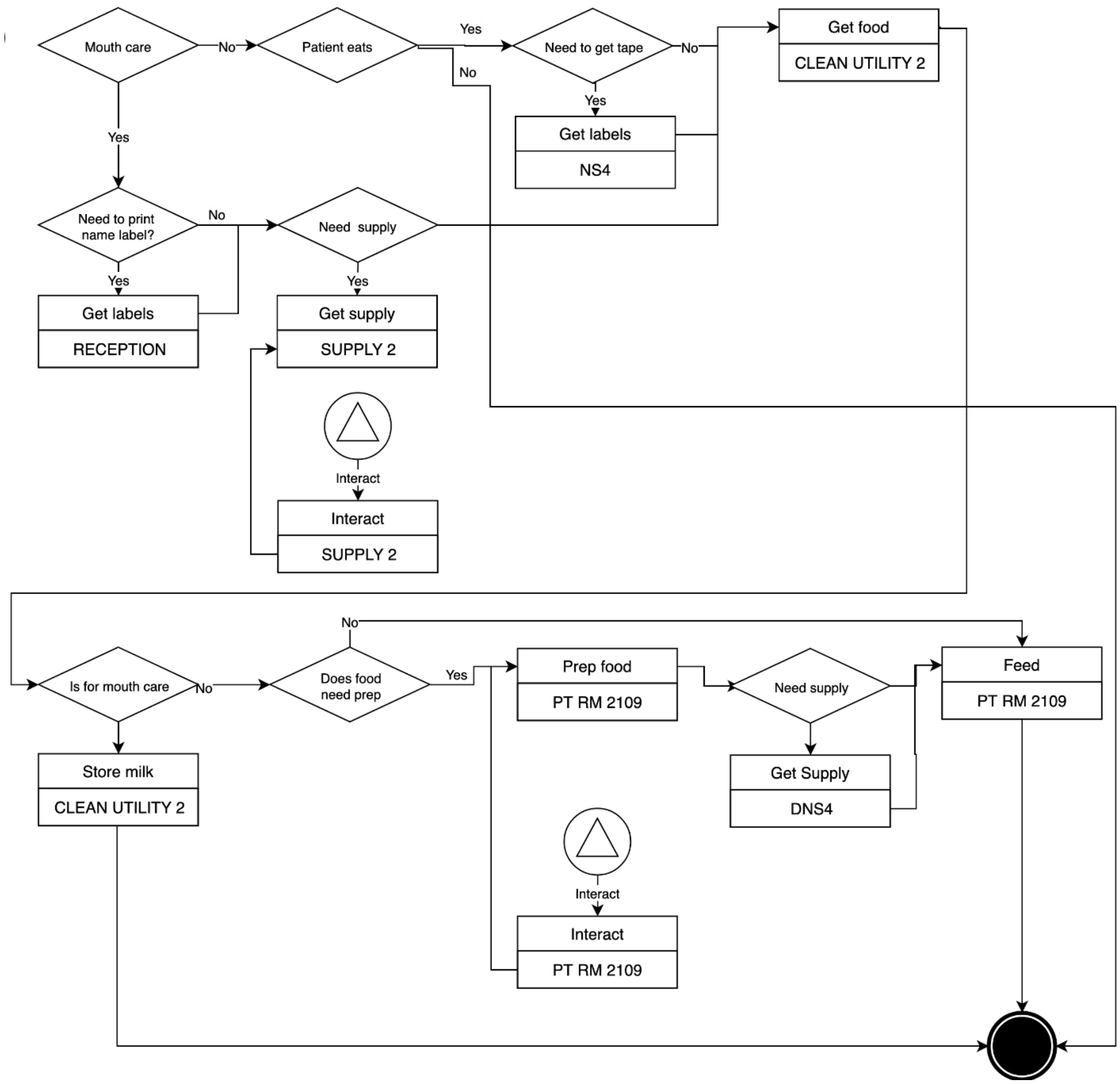


Figure 28 – Example of nutrition delivery process for a bedside nurse

Breaks: Bedside nurses take a lunch break around noon for 30 minutes in the staff break room or the café outside the unit. On some occasions, they might take a short breakfast break. Based on their individual needs, they might use the bathrooms several times during their shifts. There is only one staff toilet inside the CICU at pod1. There are two other staff toilets outside the CICU in the corridor that they might use based on the proximity and availability of bathrooms. Sometimes even the staff toilets outside the unit in the corridor are full, and they use the public toilets in the corridor. Some of the bedside nurses assigned to the patient rooms in pod3 use the bathrooms in the adjacent step-down unit since all other bathrooms are very far from them.

Every time that bedside nurses want to leave the patient side for lunch break, they find another nurse to watch their patients while they are gone. Usually, they first check in with the resource nurse to see if they are available through electronic communication (text/call) or asking in person. If the resource nurse is not available, they ask one of the neighbor nurses to watch their patients if they are not busy. They update the substitute bedside or resource nurse on the status of patients and the care plan before they leave. Upon returning from the lunch break, they get a quick update from the substitute nurse about patient status. Bedside nurses sometimes inform their neighbors while they want to take short breaks, use the bathroom as well, or leave the patient bedside for any other reasons.

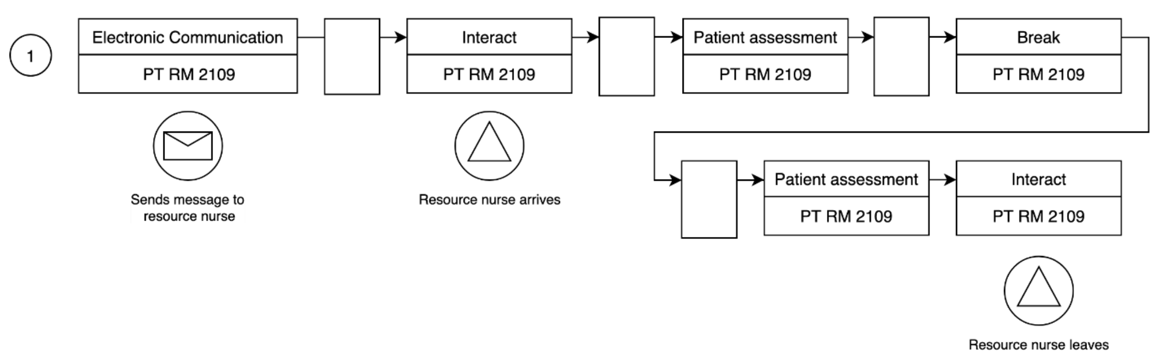


Figure 29 – Example of lunch break process for a bedside nurse

<u>Work with specialists:</u> Bedside nurses work with occupational therapists, physical therapists, speech therapists, lactation specialists, social workers on patients to prepare

patients for returning to their routines, rehabilitate, and go home. This activity happens upon the arrival of work specialists. They also assist with Electrocardiogram (EKG), Echocardiography (ECHO), ultrasound arteriography and X-Rays, or any other procedures on patients. For these procedures, they usually prepare the patients and help if necessary.

<u>Working with the care team:</u> Bedside nurses work with the care team members when they come in to check on patients. They participate in the surgery flash rounds and morning and afternoon care team rounds and update the teams on patient status. They also work with care team members every time that they come in to check on the patients. If bedside nurses become concern about the patients' condition, they inform the care team members or ask them to come and check on the patient.

<u>Work with respiratory therapists</u>: Bedside nurses are present at the respiratory therapist rounds. They inform the respiratory therapists if they become concerned about the patient respiratory condition (such as blood gas level or breathing) or respiratory equipment (oxygen levels on ventilators, ventilator alarms, oxygen tubes). They also help the respiratory therapists with intubation/extubating, transferring patients, or any respiratory-related procedures.

<u>Patient transfer and new patient handling:</u> Bedside nurses prepare patients for transfers by organizing the bed, collecting patient's belonging, printing the patient chart from reception, and packing up patients' milk from clean utility rooms. If the transferring patient is connected to ventilation equipment, bedside nurses work with the respiratory therapist to disconnect the patient from the equipment and put on the patient on an oxygen pump. They also might ask help from other nurses for transfer. After getting patient ready,

the bedside nurse takes patient bed to the step to destination. Once the patient is transferred, the bedside nurse returns to the room and clean the room. If bedside nurses are assigned to incoming patients, they prepare the room by getting the required supplies and equipment and setting up the room for patient arrival.

Report to the charge nurse: At the end of the working shift, the charge nurse visits all the patient rooms to get updates on the status of each patient from the bedside nurse.

Resource nurse drug run: At the end of the working shift, the resource nurses visit all the patient rooms and collect the remaining medication from bedside nurses.

Responding to pumps and monitors Alarms: Every time that bedside nurses hear an alarm from monitors, pumps, and equipment, they must check and make sure everything is ok. Some pump alarms indicate the completion of food or medication administration; some indicate the completion of flushing water after medication or food, and some indicate abnormalities in patients or equipment settings.

4.7 Modeling Unstructured Activity

Care providers' unstructured activities do not occur based on schedules or defined sequences. They happen in a stochastic manner depending of other ongoing activities or patient needs. For each agent in the simulation model, the occurrence of unstructured activities is simulated through Markov Chain Process modeling. A few examples of unstructured activities for bedside nurses are described here.

Patient assessment: Bedside nurses check patients frequently. It included checking on patients, IVs, wounds, patches, or the equipment connected to patients such as suction tubes, drainage tubes, pistol probes, or other connected lines. Patient assessment happens multiple times to check if the patient is stable or needs anything.

Check vitals: Bedside nurses check patients' vital signs, including temperature heart rate regularly (every 30 minutes to one hour). After checking the vitals, they chart the measurements in the patient records.

Getting supplies: Bedside nurses get most of their required supplies from one of the three supply closets, including pacifiers, diapers, pump tubes, and milk tubes. Some supplies are stored in nurse station drawers and some stored in clean utility rooms (such as cups, mixing bottles, blankets, sheets, bags). If bedside nurses cannot find the supplies, they need in the supply closet in their pod, they go to the other pods to get the supplies.

Care-related activities: Care related activities are directly or indirectly connected to patient care activities. They include cleaning patients, changing the diaper, changing sheets, repositioning patients, rearranging lines, changing tapes, changing tubes, etc.

Dropping off soiled item: Bedside nurses are responsible for removing soiled items such as dirty sheets, used equipment, and body fluids from patient bedside. They drop off the laundry at the nearest laundry container and drop off soiled equipment and body fluids at the nearest soiled utility rooms.

Family engagement: Family members visit the patients during the day. Once they arrive, the bedside nurse greets them and updates them with the patient's status. If there is not any chair for families in the patient rooms, bedside nurses go to the adjacent rooms or nurse stations to get chairs for them to sit. If the family members intend to do breastfeeding or kangaroo care, they sit in designated armchairs. Sometimes, bedside nurses go to other pods to find armchairs for family members.

Bedside nurses talk to family members at the bedside and answer their questions. If the patients' mother brings breast milk, the bedside nurse labels them, packs them, and stores them in clean utility rooms. Bedside nurses prepare the room and patient for breastfeeding and kangaroo care. It usually includes getting an armchair (if not in the room), cleaning the chair, getting pillows, sheets, and blankets, providing privacy with closing the curtains, and putting the patient in the family members' arms. They also check on patients regularly while they are with family members. If the family members want to switch for kangaroo care, the bedside nurse helps them. They also return the patient to the bed after breastfeeding and kangaroo care.

<u>Helping other nurses</u>: Bedside nurses help other nurses by checking on their pump alarms, monitoring their patients, and performing care-related activities while they are gone. They also help them with patient care activities if they needed, consult them or get supplies and equipment for them while they are busy. They can also witness for their medication at Pyxis medication stations or sign off their medications at their charting stations.

4.8 Markov Chain Process for Modeling State Transitions

Care providers' location and activity transitions in time is a stochastic process. This stochastic process modeled as a discrete-time Markov chain process in this research. Given a finite set of n states, S = (s1, s2,...,sn), an observation of a stochastic process is a successive sequence of states sampled randomly from S. S is referred to as the state space of the process. An example of such an observation in the CICU for a bedside nurse's location transitions in time could be [NS, PT RM 2109, SUPPLY, PT RM 2109, SUPPLY]. The process starts in one of the states in S and moves from one state to another in a successive manner. The transition from one state to another happens through probabilistic rules.

In general, given a sequence of the antecedent states, the predictions for the next state could be influenced by all those past states. From a modeling standpoint, it is very challenging to prove general results if such generality is to be allowed. If we assume that given the present state, the future is conditionally independent of the past, we arrive at a Markov chain process. Despite this simplifying assumption, Markov models have been demonstrated across many domains as a compelling framework for modeling stochastic processes that evolve with time (Husic & Pande, 2018).

4.8.1 Stochastic Matrix Theory

A stochastic matrix is a matrix that describes the transitions from one state to another in a Markov chain process. A chain that is currently in state si moves to state sj at the next time step with a conditional probability Pr(sj|si) = pij. These probabilities are called transition probabilities. The probabilities for all possible state transitions can be presented as a square matrix to create the stochastic matrix for a given stochastic space. A stochastic matrix is a square matrix of size n with nonnegative entries and row sums equal to 1. Figure 30 shows a stochastic matrix and its diagram presentation for an example of a 3-state space (Tolver, 2016).

$$
\begin{array}{c|ccc}
 & 1 & 2 & 3 \\
\hline
1 & & & \\
2 & & \left(\begin{matrix} 1/3 & 1/3 & 1/3 \\ 0 & 1/2 & 1/2 \\ 0 & 0 & 1 \end{matrix}\right) & \\
3 & & &
\end{array}
$$

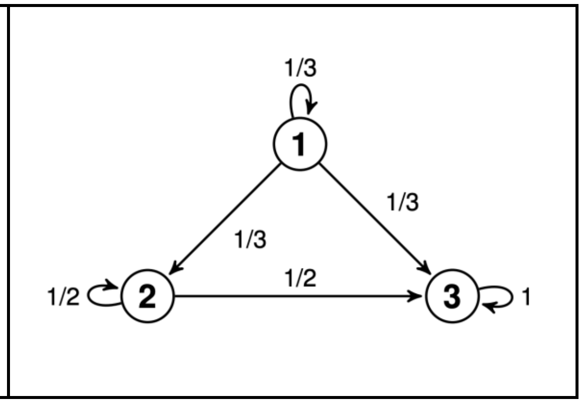


Figure 30 – An illustrative stochastic matrix and diagram for a 3-state space

4.8.2 Stochastic Matrices Estimation from Observational Data

Given a sequence of state observations, let mij denote the number of immediate occurrences of state sj after state si. We can estimate the transition probability of being in state j in time step t given the state in period t-1 been si as: pij = mij / Sigma_j(mij) (Jones, 2005). In other words, the probability of transition for si to sj is equal to the proportion of immediate occurrences of sj after si to the total number of si occurrences. This process starts from si=1 and repeats over all the n states successively to construct all the rows of the stochastic matrix one after the other. For example, for an illustrative 5-day weather condition sequence of [clouds, sun, clouds, rain, sun], the estimated stochastic matrix would be what is displayed in Figure 31.

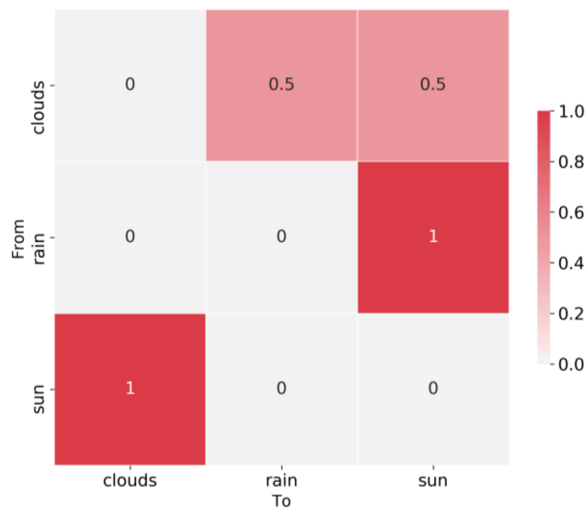


Figure 31 – Stochastic matrix for 5-day weather condition sequence of [clouds, sun, louds, rain, sun]

Figure 32, Figure 33, and Figure 34 illustrate representative stochastic matrices for location, activity, and location|activity transitions estimated from Observation #1 of the dataset for a bedside nurse. An exploratory analysis of this information alone can also reveal useful insights. For example, we can observe that the assigned patient room serves as a primary and relatively equally important departure point for trips to most of the other locations.

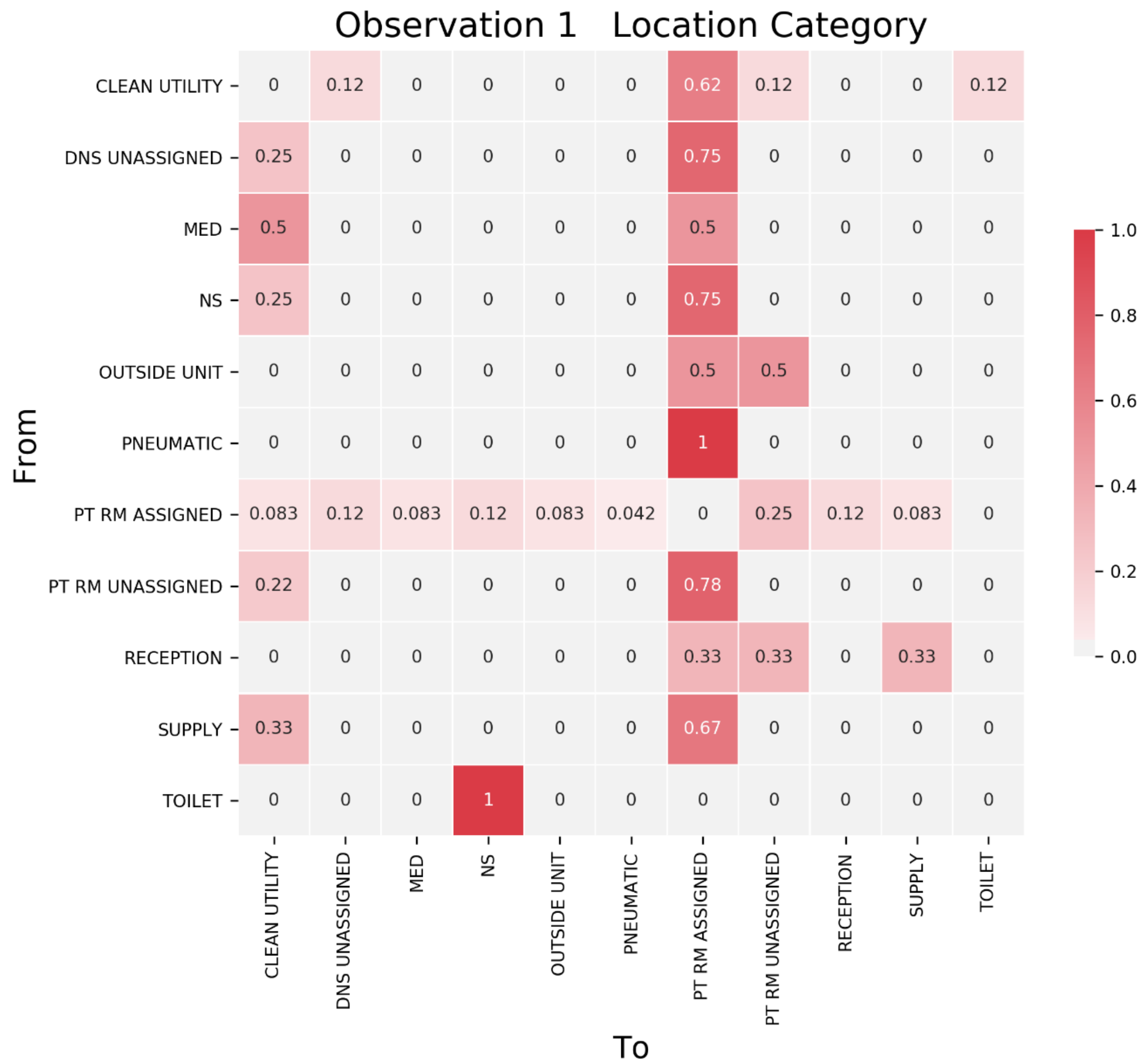


Figure 32 – Stochastic matrix estimated from observation #1 of the data set for a bedside nurse's location transitions

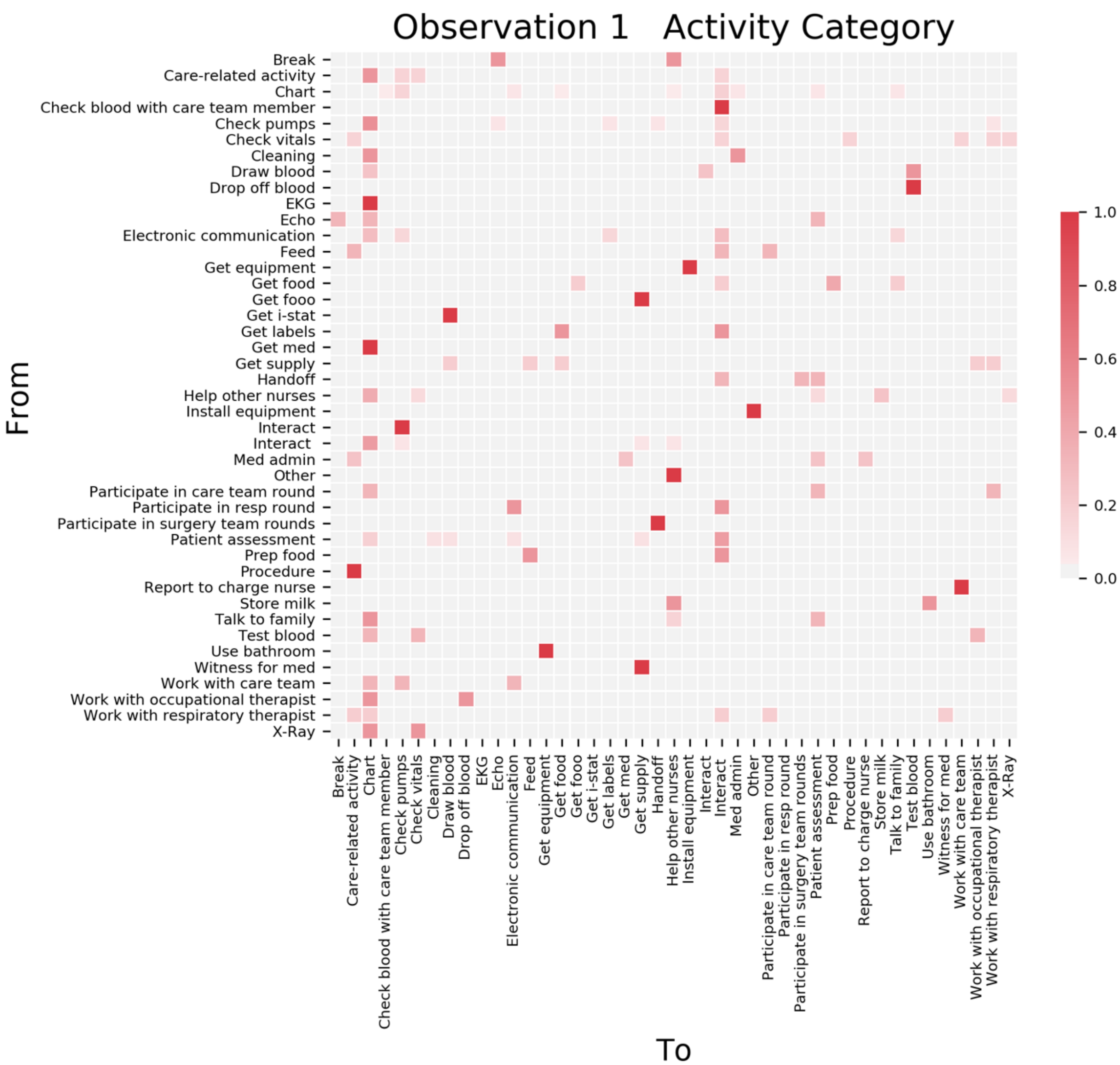


Figure 33 – Stochastic matrix estimated from observation #1 of the dataset for a bedside nurse for activity transitions

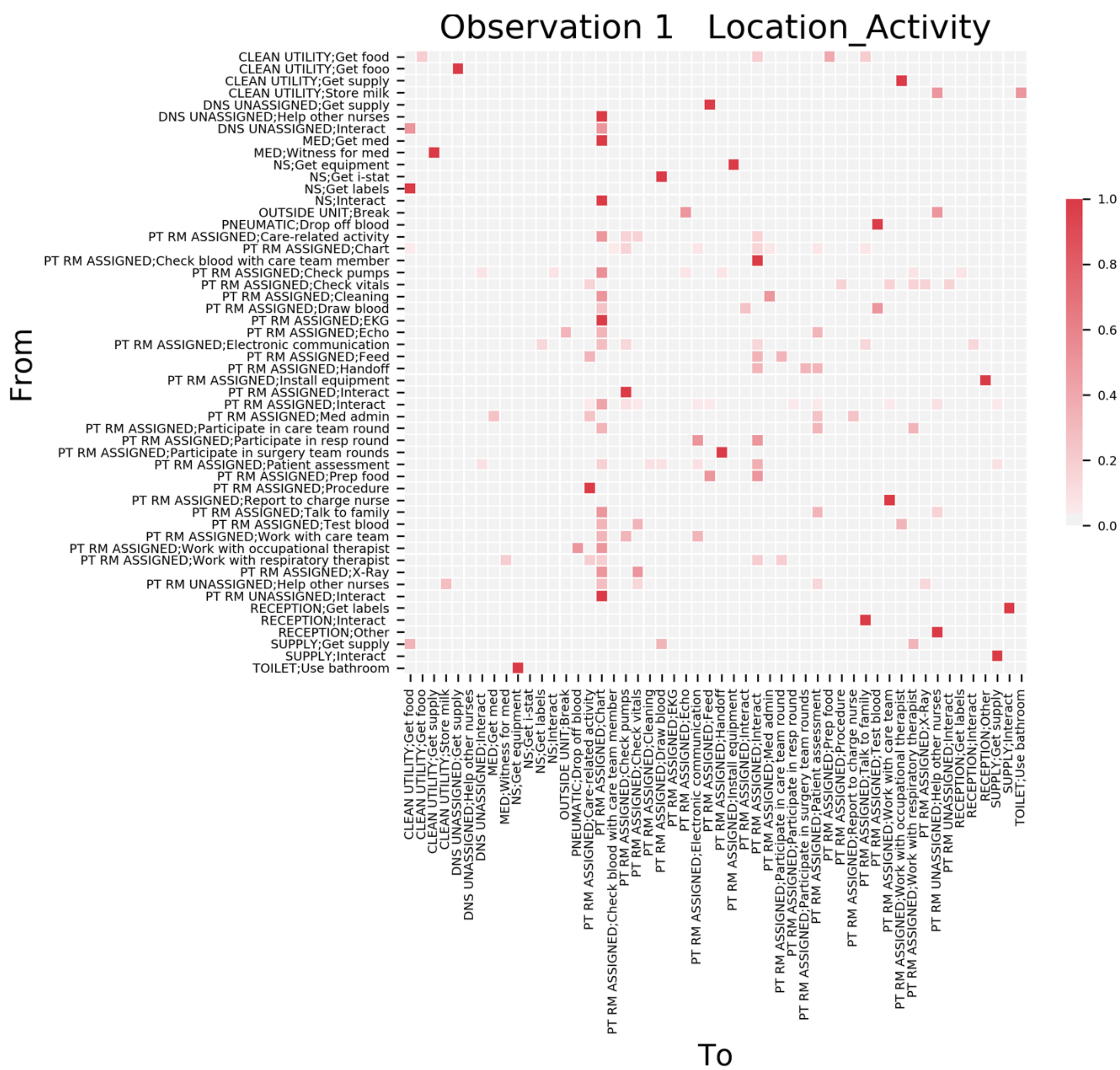


Figure 34 – Stochastic matrix estimated from observation #1 of the dataset for a bedside nurse for paired [location][activity] transitions

4.8.3 Markov Chains Process Modelling in the Simulation Platform

The collected activity and location data from site observations were used to create stochastic matrices of activity and location sequences for each observation by analyzing excel data sheets in Python programming language. The probabilities of transitions from each existing [location][activity] pair to every other existing combination of

[Activity][Location] was calculated using stochastic matrices and was saved in a text format. Additionally, the observational data was used to calculate time distribution of each activity or state and was saved as a table in text format.

A custom Java class was developed in Anylogic to implement the stochastic matrices into the simulation model for transitioning between different states. This java class has a method that takes in the stochastic matrix assigned to an agent and activity time distribution tables associated with them in text format. This method then evaluates the current [Activity][Location] pair in the simulation run and assigns the next [Activity][Location] pair to agents as their destination. The duration of the next activity in the destination is sampled from time distributions assigned to each activity. If the structured activities are not scheduled, agents select their next activity and location based on the stochastic matrices.

4.9 Model Verification and Validation

One of the challenges of an agent-based approach is related to implementing robust verification and validation techniques for model outputs. Like hypotheses, models present a possible explanation for a system that needs to be tested, verified, and validated. Verification is a process that shows whether the model corresponds to the conceptual model. Validation is a process that shows whether the model corresponds to the real world (Rand & Rust, 2011). The verification and validation processes were performed to ensure the rigor of the proposed model for this study.

The verification process happened during the model development stages. Model verification included documentation, programmatic testing, and test cases. The documentation of the model consisted of creating records of both conceptual and implemented model to be able to compare them. At multiple points during stages of model creation, the implemented model was compared with the conceptual models to ensure accuracy. By programmatic testing, the model was evaluated to ensure it functioned as what it was meant to do. The model functionality was tested out by tracing and printing out the simulation steps to identify any existing error. By test casing multiple scenarios, it was ensured that the implemented model operated according to the conceptual model.

The proposed simulation model is validated through different stages of validations, including micro-face validation, macro-face validation, empirical input validation, and empirical output validation (Rand & Rust, 2011). In the micro-face validation, we make sure that the mechanisms and properties of the implemented model correspond to the real world. For this purpose, we need to make sure that agents and their actions present a realistic model of the actual care providers. The occurrences, sequences, locations, and durations of agents' activities in the simulation model were traced and compared with the observation data. The example below shows how the sequence of activities and locations matched the observation data. Table 14 shows an example of observation data for a bedside nurse. Table 15 shows traces of activity and location data from a simulation run for a bedside nurse agent representing the same observed bedside nurse. It can be observed that records of activity and location sequences from the simulation run matches the observation data.

Table 14 – Sample observation data for a bedside nurse

Start Time	EndTime	Activity	Activity Category	Location	Location Category
16:21:55	16:22:02	Checks on pt	ptAssessment	PT RM 2105	assignedPtBed2
16:22:18	16:22:28	chart	chart	DNS2	assignedDNS
16:26:01	16:26:20	Gets a table	getEquipment	PT RM 2106	unassignedPtRms
16:26:28	16:28:07	Cleans table	cleaning	PT RM 2104	assignedWrkSrf
16:28:21	16:47:00	Changes a line (sterile)	procedure	PT RM 2104	assignedPtBed
16:47:10	16:47:17	Cleans the table	cleaning	PT RM 2104	assignedWrkSrf
16:47:28	16:48:03	Wash Hands	washHands	NS1	collNS
16:48:38	16:48:42	chart	chart	DNS2	assignedDNS

Table 15 – Sample simulation run data for a bedside nurse agent

Location	Activity	Duration(minutes)
assignedPtBed	prepForKang	2.87
assignedPtBed2	ptAssessment	1.07
unassignedPtRms	getEquipment	0.42
assignedWrkSrf	cleaning	0.46
assignedPtBed	procedure	7.77
assignedWrkSrf	cleaning	0.76
collNS	washHands	0.55
assignedDNS	chart	1.80

For macro face validation, the model was checked to ensure the aggregated system behavior and dynamics corresponded to the overall real-world behaviors. For this purpose, agents' reactions to messages received from other agents and to model events were traced to confirm that overall system behavior corresponded to real dynamics of the observed system. This confirmation was done by inspecting the traced simulation steps.

For empirical input validation, the model input data was evaluated for accuracy and correspondence to the real world through comparison with observation data. All the time-related input parameters such as activity durations and rates were evaluated and closely inspected to test if they matched the time distributions from observation data.

For empirical output validation, outputs of the simulation model were evaluated for correspondence to the real-world data. The agents' data, including agents' time spent in different activities and states in the simulation model, was recorded through model execution logs and compared with observation data. A sample of 90 simulation runs was used for validation. Each simulation run presented a 13-hour working shift. At the end of each simulation run, agent times in each state was recorded. The logs of all 90 runs were aggregated for analysis. The outputs of all simulation runs were analyzed using JMP Statistical Analysis Software to find the time distribution for different activities. Table 16 to 14 show a few examples of output validation tests for medication delivery, blood work, nutrition delivery (structured activities), charting, and patient assessment (unstructured activities) for agents representing bedside nurses. For each agent, the outputs of the simulation model were compared with data collected through observations. The distributions of observation and simulation data were inspected to make sure they presented similar trends. In a few cases, where distributions did not match the observation data, the simulation model was modified to represent the collected data better. The results showed that time distributions of activities were consistent with the data collected through observation.

Table 16 – Output validation for blood work activities

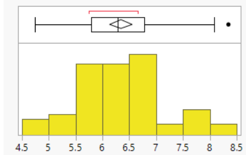
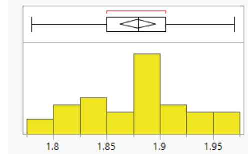
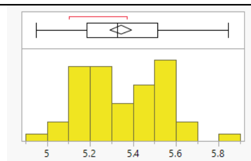
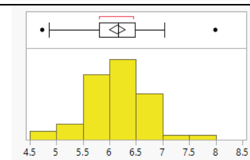
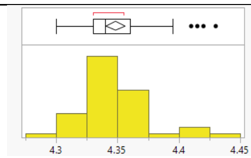
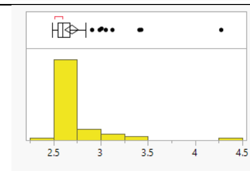
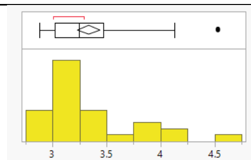
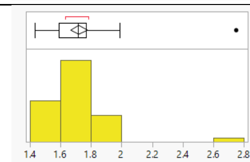
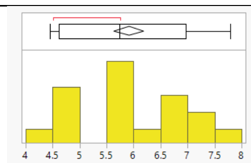
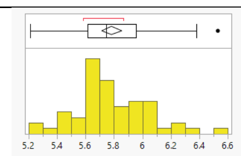
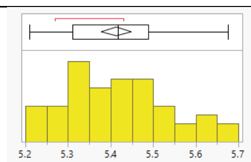
Simulation Data			Obs. Data	Simulation Data			Obs. Data
Agent	Distribution of Mean Blood Work Minutes per Occurrence	Mean (SD)	Range	Agent	Distribution of Mean Blood Work Minutes per Occurrence	Mean (SD)	Range
Bedside Nurse1		6.3(0.8)	3.4-10.45	Bedside 8		1.87(0.04)	1.4-1.8
Bedside Nurse2		5.3(0.19)	4.5-6.3	Bedside 9		6.1(0.56)	2-7.8
Bedside Nurse3		4.34(0.02)	3.8-5.7	Bedside 11		2.7(0.28)	2.2-5.2
Bedside Nurse4		3.3(0.4)	2.8-4.6	Bedside 12		1.72(0.19)	1.04-2.7
Bedside Nurse5		5.9(1.05)	4.46-7.9	Bedside 13	NA	NA	NA
Bedside Nurse6	NA	NA	NA	Bedside 14		5.78(0.26)	4.9-6.5
Bedside 7		5.41(0.12)	5-5.65				

Table 17 – Output validation for medication delivery activities

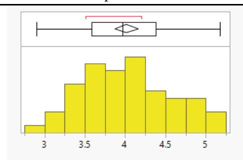
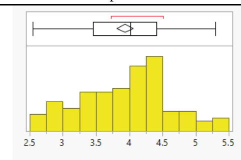
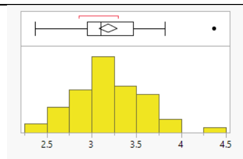
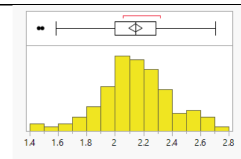
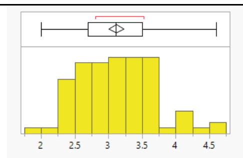
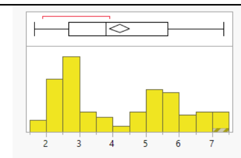
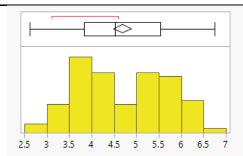
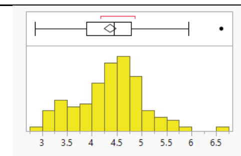
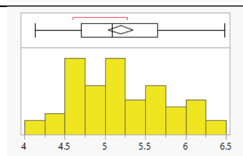
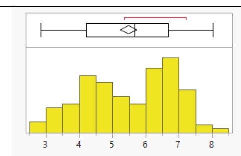
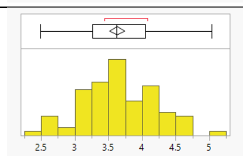
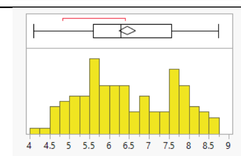
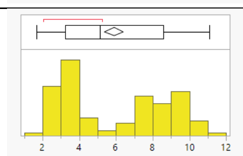
Simulation Data			Obs. Data	Simulation Data			Obs. Data
Agent	Distribution of Mean Medication Work Minutes per Occurrence	Mean(SD)	Range	Agent	Distribution of Mean Medication Work Minutes per Occurrence	Mean(SD)	Range
Bedside Nurse1		4(0.55)	2.8-5	Bedside 8		3.99(1.7)	2.79-5.78
Bedside Nurse2		3.1(0.3)	2.05-5.6	Bedside 9		2.14(0.25)	1.43-3.24
Bedside Nurse3		3.1(0.54)	1.8-4.08	Bedside 11		4.2(1.7)	2.2-7.2
Bedside Nurse4		4.6(0.9)	2.8-4.6	Bedside 12		4.36(0.67)	3.75-7.19
Bedside Nurse5		5.2(0.57)	5.1-7.13	Bedside 13		5.48(1.35)	2.83-7.3
Bedside Nurse6		3.63(0.54)	1.74-6.13	Bedside 14		6.44(1.15)	4.85-9.24
Bedside 7		2.89(2.81)	2.83-10.76				

Table 18- Output validation for nutrition delivery activities

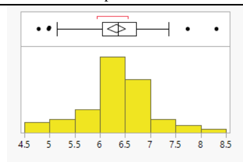
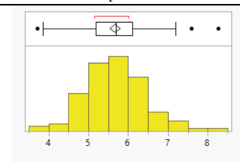
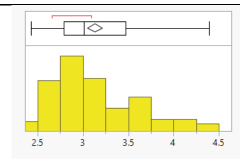
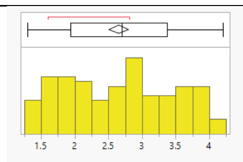
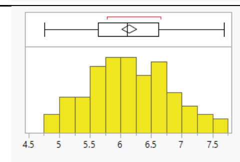
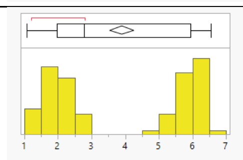
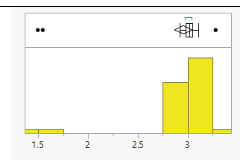
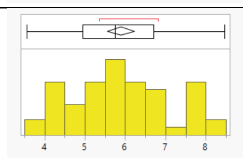
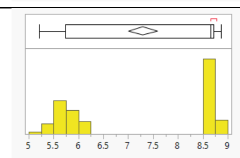
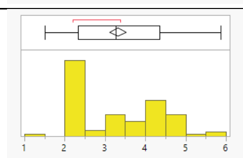
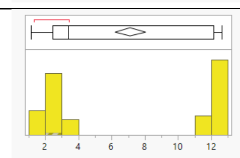
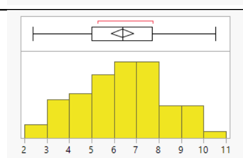
Simulation Data			Obs. Data	Simulation			Obs. Data
Agent	Distribution of Mean Nutrition Work Minutes per Occurrence	Mean(SD)	Range	Agent	Distribution of Mean Nutrition Work Minutes per Occurrence	Mean(SD)	Range
Bedside Nurse1		6.32(0.67)	4.46-7.78	Bedside 8		5.67(0.74)	2.95-7.93
Bedside Nurse2	NA	NA	NA	Bedside 9		3.13(0.46)	2.4-4.8
Bedside Nurse3		2.65(0.8)	1.07-3.89	Bedside 11		6.14(0.66)	5.15-8.08
Bedside Nurse4		3.89(2)	0.95-8.03	Bedside 12		2.9(0.3)	1-3.9
Bedside Nurse5		5.9(1.24)	3.86-9.25	Bedside 13		7.29(1.5)	5.31-8.82
Bedside Nurse6		3.32(1)	1.5-6.13	Bedside 14		7.12(4.9)	1.53-11.8
Bedside 7		6.37(1.94)	2.89-11.04				

Table 19 – Output validation for charting activities

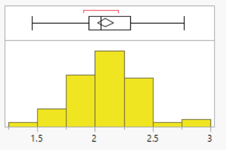
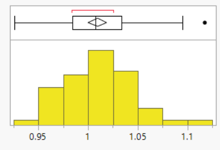
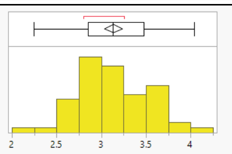
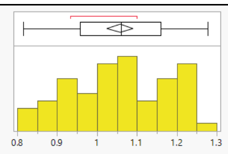
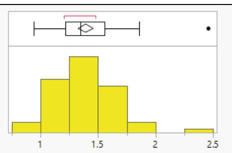
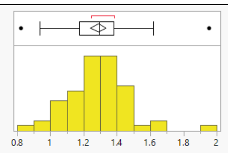
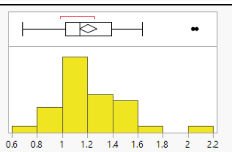
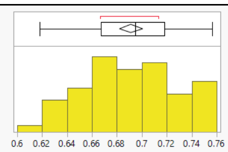
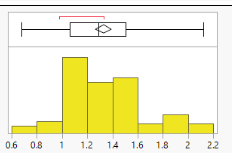
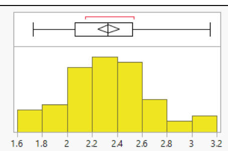
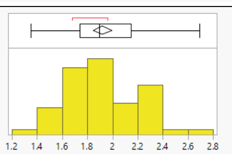
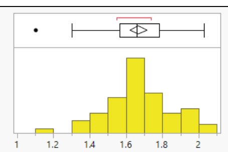
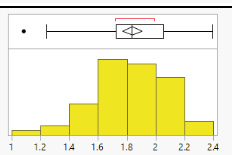
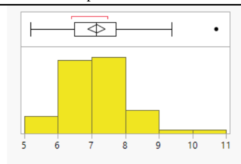
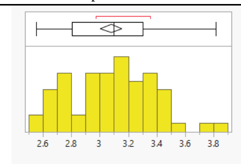
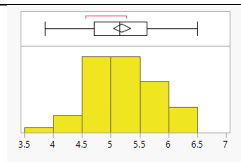
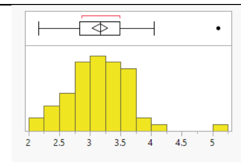
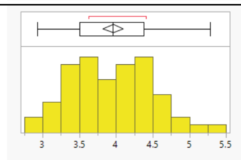
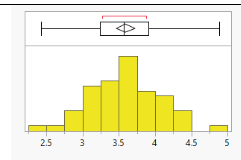
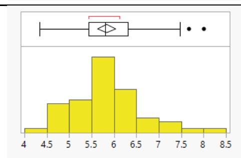
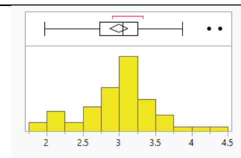
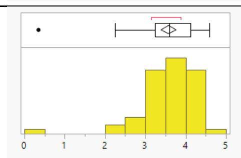
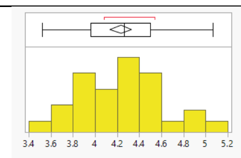
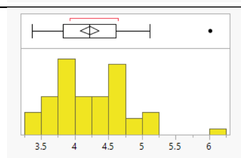
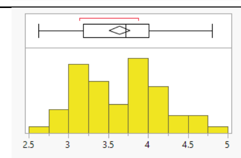
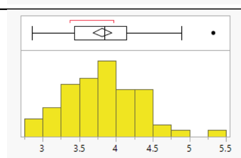
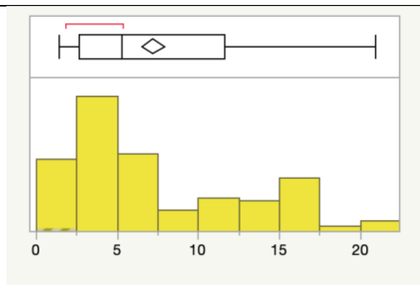
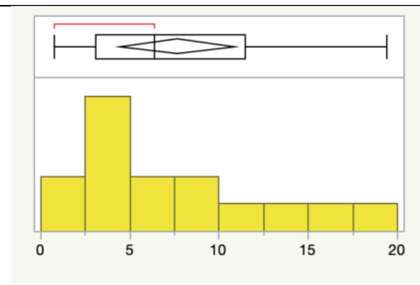
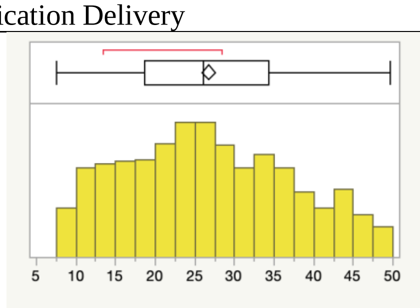
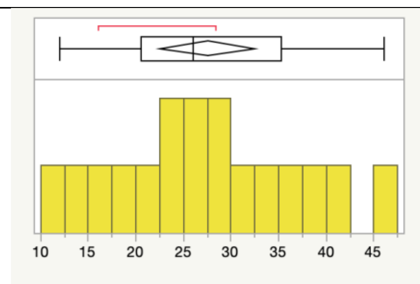
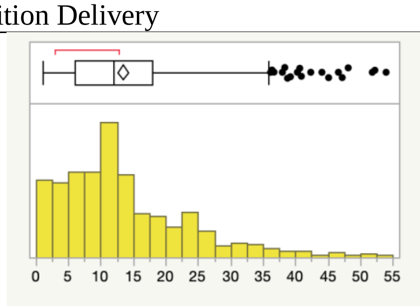
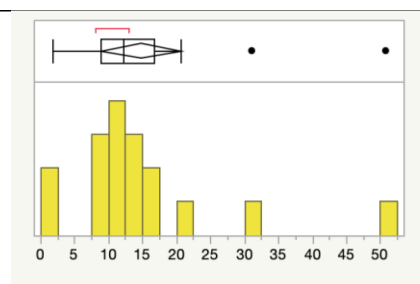
Simulation Data			Obs. Data	Simulation			Obs. Data
Agent	Distribution of Mean Charting Minutes per Occurrence	Mean(SD)	Range	Agent	Distribution of Mean Charting Minutes per Occurrence	Mean(SD)	Range
Bedside Nurse1		2.09(0.26)	0.1-6.95	Bedside 8		1(0.03)	0.07-1.54
Bedside Nurse2		3.13(0.39)	1.1-5.51	Bedside 9		1.05(0.12)	0.05-1.65
Bedside Nurse3		1.39(0.25)	0.76-3	Bedside 11		1.28(0.18)	0.98-1.7
Bedside Nurse4		1.2(0.26)	0.48-2.97	Bedside 12		0.7(0.03)	0.05-1
Bedside Nurse5		1.32(0.17)	0.88-3.01	Bedside 13		2.33(0.33)	1.23-3.14
Bedside Nurse6		1.92(0.27)	1.36-3.3	Bedside 14		1.66(0.18)	0.05-2.07
Bedside 7		1.83(0.25)	0.05-2.34				

Table 20 – Output validation for patient assessment activities

Simulation Data			Obs. Data	Simulation Data			Obs. Data
Agent	Distribution of Mean Patient Assessment per Occurrence	Mean(SD)	Range	Agent	Distribution of Mean Patient Assessment per Occurrence	Mean(SD)	Range
Bedside Nurse1		7.14(1.01)	3.98-12.01	Bedside 8		3.08(0.29)	1.05-3.5
Bedside Nurse2		5.19(0.58)	0.09-6.96	Bedside 9		3.16(0.5)	2.43-3.86
Bedside Nurse3		3.96(0.54)	2.23-6.15	Bedside 11		3.59(0.49)	1-4.3
Bedside Nurse4		5.84(0.78)	4.46-9.02	Bedside 12		2.99(0.4)	2.05-5.08
Bedside Nurse5		3.57(0.7)	0.05-4.63	Bedside 13		4.23(0.36)	3.12-6.43
Bedside Nurse6		4.22(0.53)	2-2.7.7	Bedside 14		3.64(0.51)	1.14-6.06
Bedside 7		3.81(0.49)	3.03-4.89				

The aggregated time distributions of all bedside nurse agents' activities were also compared with the aggregated time distributions of all beside nurses' observed activities through inspection for output validation. The below table shows how the simulation output on bedside nurses' activities compare to the observational activity data (Table 21). The number of data points in observational data is 17, compared to 600 data points in simulation outputs. Since the number of observational data points are limited, the probability distribution of data does not present a continuous trend in some cases. The means and standard deviations of simulation and observational data were compared for output validation.

Table 21 – Output validation of aggregated simulation data

Simulation Output	Observation Data
Blood Work	
	
Mean = 7.19; SD = 5.39	Mean = 7.64; SD = 5.82
Medication Delivery	
	
Mean = 27.5; SD = 9.7	Mean = 26.74; SD = 10.42
Nutrition Delivery	
	
Mean = 13.4; SD=9.7	Mean=14.8; SD=11.45

4.10 Simulation Outputs

The main output of the simulation model in this study is a record of encounters for each care provider in relation to all other care providers. The encounter occurrences are recorded when there is an unobstructed line of sight between two care providers within defined proximity and a defined field of view. The maximum distance for proximity is initially set at 50 feet (Szilagyi & Holland, 1980).

For each agent representing a care provider, we can measure the duration of visual exposure to all care providers within a specific diameter, as we call it “care provider-to-care provider encounter time” or for short CCE(t). We can also measure how many times that care provider has seen other care providers, as we call it “care provider to care provider encounter number” or for short CCE(n). These measures allow us to compare the assigned locations of individual care provider agents and test how layout features such as compactness and betweenness levels related to those locations impact the agents’ spatiotemporal experience. We can then compare these output metrics with the observational data and see if the care providers’ spatiotemporal experience is associated with the occurrence of unplanned interactions.

The measurement of care providers’ spatiotemporal experience with defined encounter metrics can be explained through an example. In this example, we want to examine the spatiotemporal experience of agent A and agent B in relation to all other agents. For each agent, we can measure how many other agents they have encountered during simulation runs (For example, agent A has encountered 6 other agents, whereas agent B has encountered 4 other agents).

We can also set a threshold for what is perceived a long encounter time based on all the recorded encounter times and evaluate if two agents had encounter episodes with long durations. Agent A has long encounter times with more agents (agent B, C and H), compared to Agent B who has long encounter time to agent D and A. Therefore, we can say that agent A is more likely to have unplanned seated interactions, compared to agent B.

The average number of encounter episodes per target agent could be used to evaluate probabilities of on-move interactions. For example, the average encounter number per agent for agent A is 1.75. For agent B, the average encounter number per agent is 1. Therefore, we can assume that agent A is more likely to have on-move interactions.

An averaged encounter episode for all individual agents can be calculated as an indicator of overall layout performance measure for care provider-to-care provider encounters.

The simulation model was set to run for 30 daytime shifts with a total of 3900 hours in a 6:30 am to 7:30 pm schedule. The encounter episodes reported in this study were measured with a 50-feet distance parameter and 200-degree field of view and were evaluated every 500 milliseconds (0.5 seconds). For each agent representing a bedside nurse, encounters episodes were measured in relation to all other agents, including other bedside nurses, resource nurses, care team members (nurse practitioners and attending doctors) respiratory therapists, and the charge nurse. At the end of the simulation run, the outputs of care provider agent's encounters were written to external excel files. The results of all 30 simulation runs were aggregated and analyzed to understand the distribution of results.

4.10.1 Integration of spatial analysis logics for calculating simulation outputs

Currently, there is no existing function to examine the line of sight between two agents in the Anylogic simulation environment. Anylogic software allows users to create their own Java classes for any required functionality. In order to evaluate the line of sight between agents, a custom java class was created to test whether one agent can see another agent. The methods in the line of sight class (LOS) test three requirements to see if two agents can see each other. The first test checks the distance between the two agents to make sure they are within a predefined distance (dmax). The second test examines whether the target agent is in the horizontal field of view of a given agent using a customizable field of view degrees (angleMax). For example, the field of view (FoV) can be set to 120 degrees for including only binocular visual field (intersection of monocular visual fields of both eyes), or 200 degrees for total visual field (union of monocular visual fields of both eyes), or to 360 degrees to cover line of sight in any direction.

Figure 35 shows the calculations for determining the field of view requirements to test if Agent A can see agent B based on a 120-degree field of view and 35-distance threshold. The red vectors show the field of view of agent B with 120 degree. The green line connects the center location of Agent A to agent B. The purple line (Hline) shows the X axis.

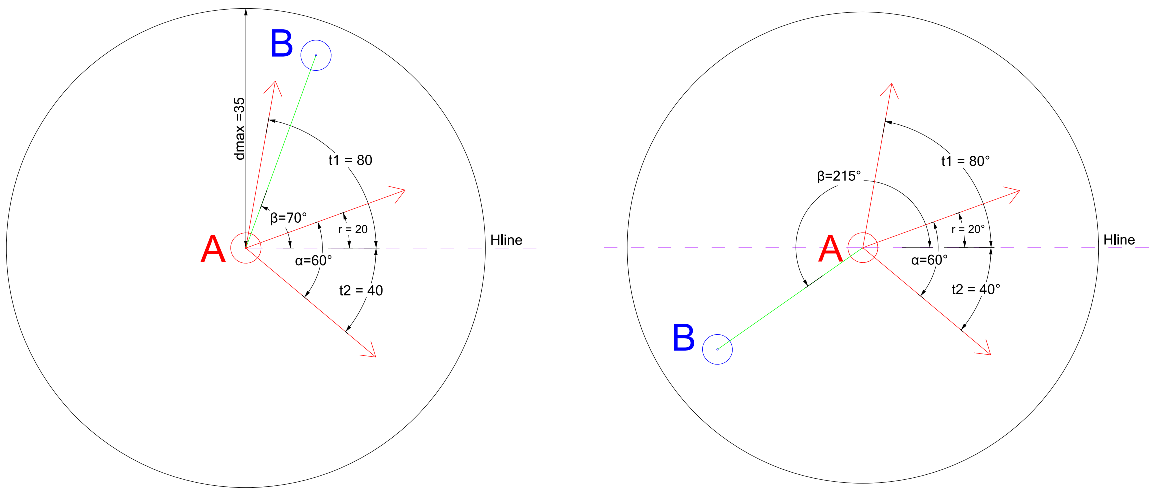


Figure 35 – Example of FoV check based on 120 degree

Based on the calculations in the above diagram, agent B is in the FoV of A if $t1 \leq \beta \leq t2$, where:

$$\alpha = FoV/2$$

β = Angle between the line connecting A and B (green line) and the horizontal line showing the X axis (Hline)

r = Horizontal rotation of A (angle between horizontal line and direction of agent A)

$$t1 = r + \alpha \ ; \ t2 = 2\alpha - t1$$

After checking for the distance and FoV requirements, the LOS definition checks for any physical obstacles that might block the direct line of sight between the two agents. If all the three above requirements are met, then the LOS function confirms the existence of a direct line of sight between the two agents and records an encounter episode.

The defined LOS java class has a method called “isInSight” wich can return a Boolean value as the result of the above tests based on the input parameters. The isInSight method can be called at the agent level and be triggered by defined events. For example, we can define an event inside a specified agent which evaluates the above tests through isInSight method every 30 seconds for that agent. The input parameters for this method include distance (dmax), angle (angleMax), the origin(o), which is the current agent, the target (t) which could be another agent or a specified point, and a set of visual obstacles (wallLines) that can block the view from “o” to “t”. This method also has other parameters for visualizing the results, which can be set to true to turn on the visualization. The “isInSight” method returns a Boolean value reporting whether an encounter episode was formed between the origin and target agents.

Every time that this method gets called, the Boolean output value is recorded in an array list collection. This array list can be defined using the existing Anylogic components. The list of these Boolean values can be accessed at the end of the simulation run with another method defined in the LOS java class called “seenHisAnalytics”. This method writes the results to external Excel files with names of “o” and “t” agents. The output data files include the total duration of encounters to “t” agent, the list of Boolean values for every defined time step, and the duration of each encounter episode. This data can be further analyzed through post-processing to gain insights and draw conclusions.

CHAPTER 5. RESULTS

This chapter includes the results of the simulation output analysis and explains the associations between encounter measures and layout attributes.

5.1 Impact of Layout on Bedside Nurses' Interactions

Based on the observational data collected by this study, the interactions among bedside nurses in the CICU can be divided to three categories. The first category was planned interactions. The planned interactions occurred when care providers wanted to request help for patient care activities, ask questions, consult, or leave their patients to others. Planned interactions were distributed across all locations and happened anywhere. In such situations, nurses first interact with others from their location. If they could not get an available person around them, they then might walk further and find the help they need.

The observation data shows that nurses with one-patient assignment had more planned interactions (except for observation 9 and 14 for male nurses). One-patient assignments are for patients in critical conditions and complex cases. In these cases, when patients' condition has a higher complexity, nurses tend to seek help and consultation more often. Therefore, it is safe to assume the occurrence of this kind of interactions depends more on patient needs than space.

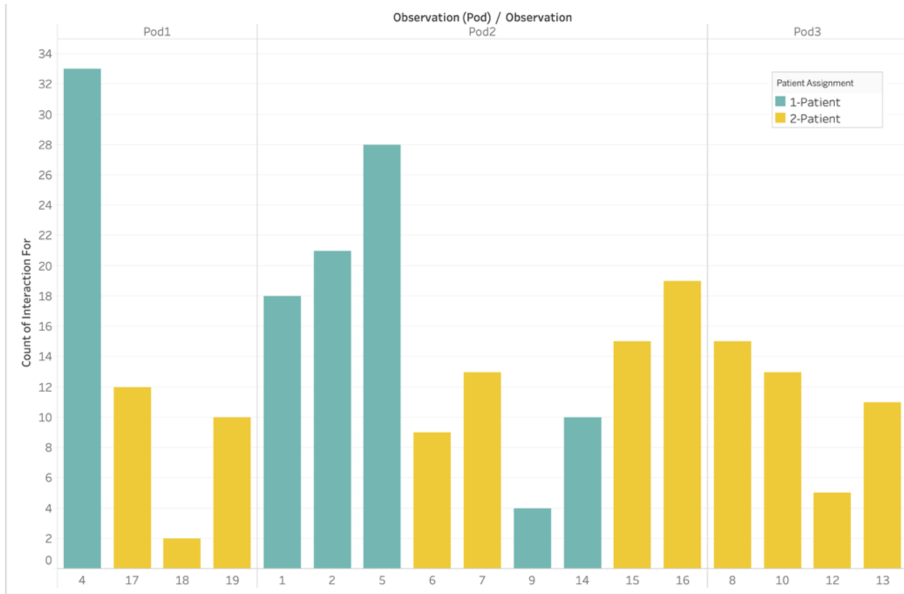


Figure 36 – Occurrences of planned interactions for one and 2-patient assignments

The second category coded as "Talking" in data included casual conversations about patient conditions or personal conversations. This kind of interaction involved casual conversations between individuals when they were not engaged in other activities. Based on the observations, interactions of this type mostly occurred while bedside nurses were at their assigned nurse stations, where nurses spent a considerable amount of time. Data showed that 40% of seated interactions happened at assigned nurse stations, 22% at unassigned nurse stations, and 17% at central nurse stations and the workroom. In this study, we call this category "seated" interactions. Bedside nurses have seated interactions with their neighbor nurses or other care providers at adjacent nurse stations. Therefore, the higher the number of visible neighbor nurses around them, the higher are the chances of occurrence of casual conversations.

The third group of interactions was on-move interactions, which happened while nurses were walking, or other nurses and care providers walked by or stopped for a quick talk or checking in. These kinds of interactions only lasted a few seconds and usually involved quick knowledge transfer, check-ins, or exchanging pleasantries. Most of these interactions happened while a bedside nurse was sitting at their decentralized nurse station or performed care activities at the bedside while other care providers or nurses passed by. Proximity to areas with higher rates of movements facilitated these kinds of interactions.

The second and third categories of interactions mentioned above are different from planned interactions and usually happen in an unplanned manner. In this study, we call the combination of these two categories "unplanned interactions". Considering the mechanism of these unplanned interactions, we can hypothesize how space would facilitate the occurrence of such interactions.

The below diagram shows movement density across the CICU layout for all observed movement paths. The heat map colors represent the number of movement paths crossing each point. Red represents areas with the movement paths crossing through, and blue represents areas with the fewest number of movement paths. As can be seen, pod2 has the highest traffic. One possible reason could be that pod2 is in between pod1 and pod3. All the movement paths from pod1 to 3, from pod 3 to pod1, and most traffic from pod1 to areas outside of the unit go through this pod. Another reason could be that the nurse stations in pod2 are the base location for the resource nurses, charge nurse, and most of the care team members and therefore draw the traffic to these pods.

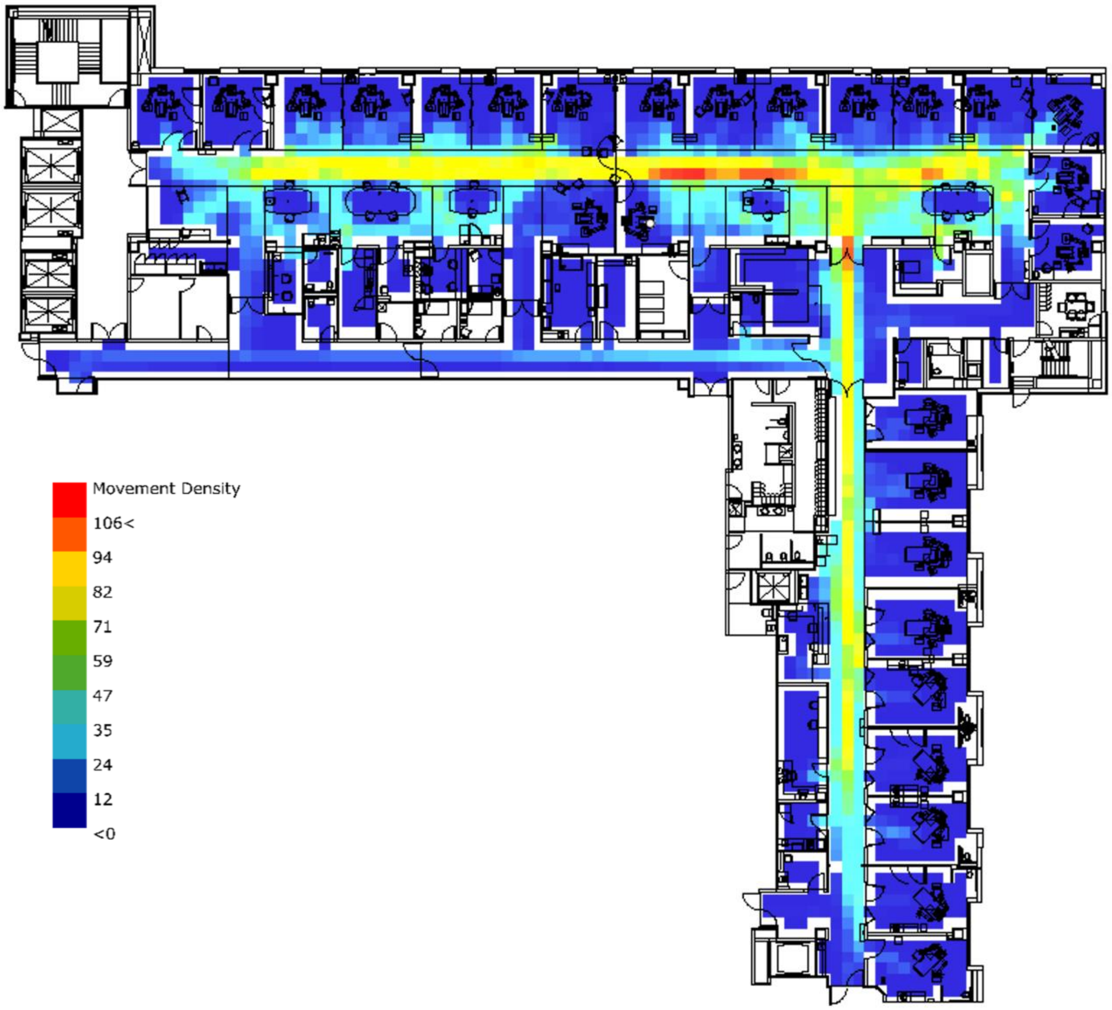


Figure 37 – Movement density map

Based on the above movement density map, we can observe that nurses in pod had2 more unplanned interactions compared to pod1 and pod3. As can be seen observations 5, 6, 7, 15, and 16 in pod2, as well as observations 18 and 8 in pod3 and 1, had the most unplanned interactions. If we look at the layout of the unit, we can see that the observations 18 and 8 in pod1 and 3 are in rooms immediately attached to pod2 and therefore, share some spatial qualities of pod 2 including centrality and betweenness. The below diagram shows the number of unplanned interactions in pod1, 2 and 3.

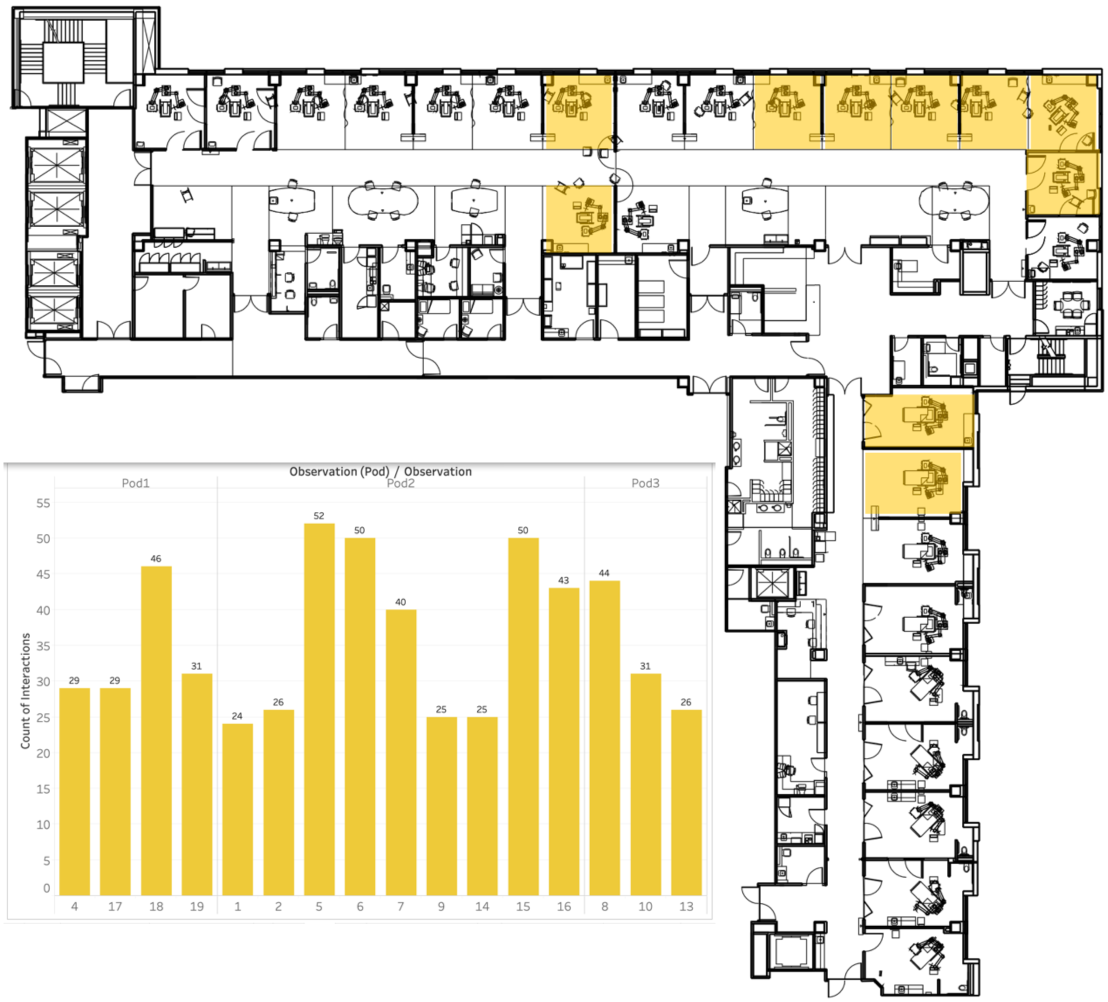


Figure 38 – Observations with higher unplanned interactions

The collected observational data confirms this finding. Based on a GLM test with a Poisson distribution for counts of unplanned interactions as the response variable and a logarithmic link function for bedside nurses' location (pod1, pod2, and pod3) as the explanatory variable, bedside nurses assigned to pod2 had significantly higher levels of unplanned interactions (**Error! Not a valid bookmark self-reference.**). Bedside nurses in pod2 had a 95% chance that the log number of their unplanned interactions increases by 0.05 to 0.32.

Table 22 – The results of GLM for comparing bedside nurses' unplanned interactions between pod1, pod2, and pod3

Term	Estimate	Std Error	L-R ChiSquare	Prob>ChiSq	Lower CL	Upper CL
Intercept	3.6348423	0.0524928	1759.0822	<.0001*	3.5300531	3.735897
Pod[1]	-0.070015	0.0768124	0.842693	0.3586	-0.223091	0.07836
Pod[2]	0.1883495	0.0676534	7.6812158	0.0056*	0.0553728	0.3207884

5.2 Aggregated CCEt

Figure 39 shows the simulation outputs for encounter episodes of agent1 representing a bedside nurse located at patient room 2109, in relation to bedside nurse agent 8, based in rooms 2115 and 2117. The assigned patient rooms to these two agents (patient rooms 2109, 2115 and 2117) are in pod 2 in the CICU. This figure shows the distribution of CCEt values for all simulation runs, which ranged between 17.40 to 61.13 minutes with a mean of 40.39 minutes. It means that across all simulation runs, agent1 has encountered agent8 for at least a total of 17.40 minutes during a working shift.

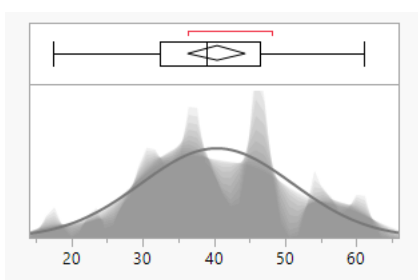


Figure 39 – Total CCEt distribution for bedside agent 1 to bedside agent 8

A similar analysis was conducted for all pairs of agents in the simulation model to understand the overall spatial experience of individual agents based on their assigned locations in the layout. The total CCEt values measured for each bedside nurse agent per other bedside nurse agent ranged between 0 and 457.17 minutes, with 75% under 24.34 minutes, a median of 5 minutes, and a mean of 30.16 minutes (Figure 40). The total CCEt for each bedside nurse agent per other care provider agents (excluding bedside nurses) ranged between 0 and 215.8 minutes, with 75% below 55.48 minutes, a median of 28.3 minutes, and a mean of 39.63 minutes (Figure 41). Care team members, respiratory therapists, resource nurses, and the charge nurses move globally within the CICU. They also have more idle time compared to bedside nurses when they stay in the same place for a longer duration of time. Bedside nurses' movements are mostly local, and they continuously switch between locations for different tasks even within the patient rooms areas. For these reasons, the total durations of bedside nurse agents CCEt are in average longer for care providers other than other bedside nurses.

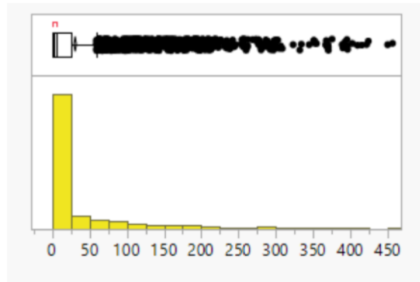


Figure 40 – Distribution of total CCEt for bedside nurse agents per other bedside nurse agents (Minutes)

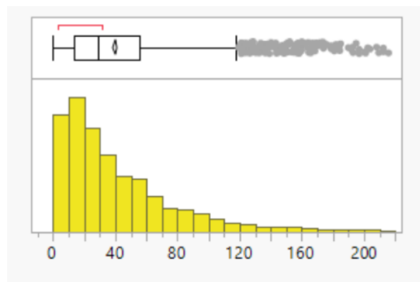


Figure 41 – Distribution of total CCEt for bedside nurse agents3 per other care provider agents (Minutes)

Based on the assumptions of this study, bedside nurse agents assigned to pod2 are more likely to have longer durations of encounter per other bedside nurse agents, compared to those in pod1 and pod3. To test this hypothesis using the outputs of the simulation model, the bedside nurses' CCEt measures in pod1, pod2, and pod3 were compared. Since the distribution of CCEt values was not normal (Figure 40and Figure 41), a non-parametric Kruskal-Wallis test was performed to compare bedside nurse agents in three pods. The results of the analysis showed that bedside nurse agents assigned to pod2 ranked significantly higher in their CCEt with other bedside nurses (chi square=48, df =2, $p<0.001$) with a mean rank score of 2290.22, compared to those located in pod1(score mean = 2503) and pod3 (score mean=2179.60) (Table 23). Bedside nurse agents assigned to pod3 experienced significantly shorter CCEts compared to those assigned to pod2 (p<0.0001) and pod1(p<0.05) (Table 24).

Table 23 – Kruskal-Wallis test for comparing bedside nurse agents' CCEt with other bedside nurse agents in pod1, pod2, and pod3

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
1	1440	3297911	3367440	2290.22	-1.632
2	1805	4517911	4220993	2503.00	6.607
3	1431	3119004	3346394	2179.60	-5.345

Table 24 – Nonparametric comparison of bedside nurse agents' CCEt with other bedside nurse agents for each pair of pods

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
2	1	151.522	33.10344	4.57723	<.0001*	1.00833	0.45833	1.61667
3	1	-72.224	30.94079	-2.33425	0.0196*	-0.34167	-0.72500	-0.04167
3	2	-219.935	33.06947	-6.65069	<.0001*	-1.59167	-2.20000	-1.00000

Another assumption of this study was that bedside nurse agents in pod2 are more likely to have longer durations of encounter per other care providers agents (including care team members, resource nurses, the charge nurse and respiratory therapists), compared to those in pod1 and pod3. A non-parametric Kruskal-Wallis test was performed to compare bedside nurse agents in three pods. The results of the analysis showed that bedside nurse agents assigned to pod2 ranked significantly higher in their CCEt with other care providers (chi square=1006.62, df =2, p<0.001) with a mean rank score of 2449.63, compared to those located in pod1(score mean = 2060.97) and pod3 (score mean=1100.25) (Table 25).

Bedside nurse agents in pod3 had significantly shorter CCEt, compared to those in pod2 and pod1 (p<0.001) (Table 26).

Table 25 - Kruskal-Wallis test for comparing bedside nurse agents' CCEt with other care provider agents in pod1, pod2, and pod3

Level	Count	Score Sum	Expected Score	Score Mean	(Mean-Mean0)/Std0
1	1220	2514385	2321050	2060.97	6.115
2	1393	3412334	2650183	2449.63	23.355
3	1191	1310392	2265878	1100.25	-30.417

Table 26 - Nonparametric comparison of bedside nurse agents' CCEt with other bedside nurse agents for each pair of pods

Level	- Level	Score Mean Difference	Std Err Dif	Z	p-Value	Hodges-Lehmann	Lower CL	Upper CL
2	1	296.822	29.58326	10.0334	<.0001*	12.4250	9.9833	14.9083
3	1	-641.127	28.35694	-22.6092	<.0001*	-17.5167	-19.1667	-15.9000
3	2	-886.378	29.44426	-30.1036	<.0001*	-32.9167	-35.0750	-30.7750

5.3 CCEt Episodes

Out of the 655,024 recorded single encounter episodes for bedside nurse agents, 88% had durations below 10 minutes. Also, 82% of all records had durations below one minute, and 75% had durations below 20 seconds. The recorded durations for single encounter episodes varied between 0.5 seconds and 144.02 minutes. It should be considered that the step duration for recording encounter episodes in the simulation model was set at 0.5 seconds, so the durations below 0.5 seconds are not recorded.

For this study, encounter episodes longer 10 minutes (CCEt $\geq$ 10) were considered as long episodes. The recorded encounter durations were analyzed to calculate the number of target agents with long encounters for each bedside nurse agents (numCCEt10). Long encounter episodes between each bedside nurse agents and another agent were verified if more than one long episode was recorded in each of the 30 simulation runs (Table 27). The analysis of data showed that mean total CCEt and numCCEt10 were correlated ($p<0.05$). Bedside nurse agents who had higher mean total duration of exposure to other care providers had also higher numCCEt10.

Table 27 – Encounter episodes with durations above 10 minutes

	ROOM	2109	2110	2104-2105	2101-2102	2103	2107-2108	2112-2113	2115-2117	2114-2216	2119-2120	2122-2123	2124-2125	2126-2127
	POD	2	2	1	1	1	1	2	2	2	3	3	3	3
	Agent	**BSN1**	**BSN2**	**BSN3**	**BSN4**	**BSN5**	**BSN6**	**BSN7**	**BSN8**	**BSN9**	**BSN11**	**BSN12**	**BSN13**	**BSN14**
Target Agents	**BSN1**													
	BSN2													
	BSN3													
	BSN4													
	BSN5													
	BSN6													
	BSN7													
	BSN8													
	BSN9													
	BSN11													
	BSN12													
	BSN13													
	BSN14													
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	NP2													
	RN1													
	RN2													
	RESP1													
	RESP2													
	RESP3													
	CHN													

Based on the assumptions of this study, bedside nurse agents assigned to pod2 are more likely to have long episodes of encounter with more bedside nurse agents or higher numCCEt10, compared to those in pod1 and pod3. To test this hypothesis using the outputs of the simulation model, a GLM was fitted to the output data with a Poisson distribution of numCCEt10 as the response variable and the location (pod1, pod2, and pod3) as the explanatory variable. Based on the results of the GLM model, bedside nurse agents assigned to pod2 had significantly higher numCCEt10 to other bedside nurse agents ($p<0.05$), compared to those assigned to pod1 and pod3. For bedside nurse agents assigned to pod2, there is a 95% chance that the log of numCCEt10 will increase by an amount between 0.07 to 0.78 (Table 28).

Table 28 - Results of the GLM model for comparing bedside nurses' agents numCCEt10 to other bedside nurse agents in pod1, pod2, and pod3

Term	Estimate	Std Error	L-R ChiSquare	Prob>ChiSq	Lower CL	Upper CL
Intercept	1.3647815	0.1475102	51.126165	<.0001*	1.0579317	1.6386645
Pod[1]	0.0215128	0.2063797	0.0108333	0.9171	-0.397947	0.4185696
Pod[2]	0.4269779	0.1813019	5.5808545	0.0182*	0.0729974	0.78834

5.4 Aggregated CCEn

Figure 42 shows the simulation outputs for encounter episodes of agent1 representing a bedside nurse located at patient room 2109, in relation to bedside nurse agent 8, based in rooms 2115 and 2117. The assigned patient rooms to these two agents (patient rooms 2109, 2115 and 2117) are in pod 2 in the CICU. It shows the distribution of CCEn for all simulation runs, which ranged between 60 and 167 times with a mean of 101.16

times. It means that that across all simulation runs, agent1 has encountered agent8 at least 60 times during the working shift.

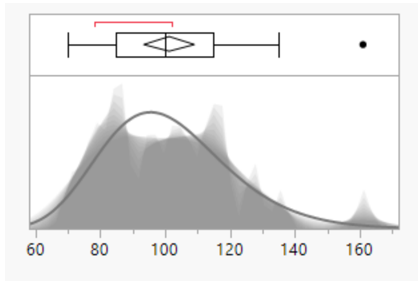


Figure 42 – Total CCEn distribution for bedside agent 1 to bedside agent 8

A similar analysis was conducted for all pairs of agents in the simulation model to understand the overall spatial experience of individual agents based on their assigned locations in the layout. The total CCEn for each bedside nurse agent per other bedside nurse agent ranged between 0 and 659 times minutes, with 75% under 87.75 times, a median of 19 times, and a mean of 65 times (Figure 43). The total CCEt for each bedside nurse agent per other care provider agents (excluding bedside nurses) ranged between 0 and 479 times, with 75% below 134 times, a median of 79 times, and a mean of 98.28 times (Figure 44). These trends are similar to what was observed for CCEt values for bedside nurse and other care provider agents. Because of global movements care team members, resource nurses, and respiratory therapist agents move globally, bedside nurse agents encounter them more often compared to other bedside nurse agents.

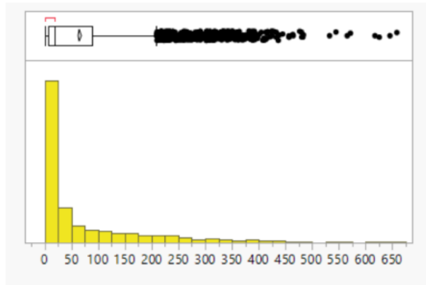


Figure 43 - Distribution of total CCEn for bedside nurse agents per other bedside nurse agents (count)

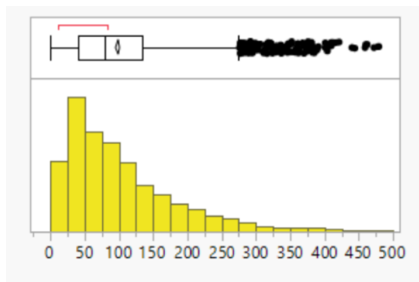


Figure 44 - Distribution of total CCEn for bedside nurse agents per other care providers (count)

Based on the assumptions of this study, bedside nurse agents assigned to pod2 are more likely to have higher counts of encounter per other bedside nurse agents, compared to those in pod1 and pod3. To test this hypothesis using the outputs of the simulation model, a GLM was fitted to the output data with a Poisson distribution of CCEn as the response variable and the location (pod1, pod2, and pod3) as the explanatory variable. Based on the results of the GLM model, bedside nurse agents assigned to pod2 had significantly higher counts of encounters (CCEn) per other bedside nurse agents ($p<0.0001$), compared to those assigned to pod1 and pod3. For bedside nurse agents assigned to pod2, there is a 95% chance that the log of CCEn to other bedside nurses will increase by an amount between 0.34 to 0.35 (Table 29).

Table 29 – Results of the GLM model for comparing bedside nurses' agents CCEn to other bedside nurse agents in pod1, pod2, and pod3

Table 1	**Estimate**	**Std Error**	**L-R ChiSquare**	**Prob>ChiSq**	**Lower CL**	**Upper CL**
Intercept	4.1190291	0.0019472	4474939.2	<.0001*	4.1152118	4.1228465
pod[1]	0.0653931	0.002705	584.41814	<.0001*	0.06009	0.0706962
pod[2]	0.3484507	0.0024312	20541.831	<.0001*	0.3436844	0.353217

Another assumption of this study was that nurse agents assigned to pod2 are more likely to have higher counts of encounter per other care provider agents (care team members, resource nurses, respiratory therapists, and the charge nurse), compared to those in pod1 and pod3. To test this hypothesis using the outputs of the simulation model, a GLM was fitted to the output data with a Poisson distribution of CCEn as the response variable and the location (pod1, pod2, and pod3) as the explanatory variable. Based on the results of the GLM model, bedside nurse agents assigned to pod2 had significantly higher counts of encounters (CCEn) per other care provider agents ($p<0.0001$), compared to those assigned to pod1 and pod3. For bedside nurse agents assigned to pod2, there is a 95% chance that the log of CCEn to other care providers will increase by an amount between 0.34 to 0.35.

Table 30- Results of the GLM model for comparing bedside nurses' agents CCEn to other care provider agents in pod1, pod2, and pod3

Term	**Estimate**	**Std Error**	**L-R ChiSquare**	**Prob>ChiSq**	**Lower CL**	**Upper CL**
Intercept	4.4642385	0.0018336	5927748.3	<.0001*	4.4606435	4.4678334
pod[1]	0.1393979	0.0024815	3155.4924	<.0001*	0.1345326	0.1442632
pod[2]	0.3458115	0.0023256	22110.105	<.0001*	0.3412519	0.3503712

5.5 Number of Encountered Agents

The outputs of the simulation model show that all bedside nurse agents encountered almost all other bedside nurses (between 91% to100%) at least once at some point during the working shift across all simulation runs. The bedside nurse agents in all three pods also encountered all other care providers (including care team members, respiratory therapists, resource nurses, and the charge nurse) at least once during the working shift across all simulation runs. There was not any significant difference between the number of agents encountered by each bedside nurse agents between the three pods. This similarity among agents in all pods is somewhat counter-intuitive considering the significant differences in duration of encounters between the three pods, with pod2 standing out as having the highest mean total encounter durations because of the centrality and betweenness.

The placement of attractor locations such as care teamwork room and staff toilet in pod1 and staff break room in pod3 brings other care provider agents occasionally to these locations, which are not otherwise centrally located or on the path to other locations. The other attractor locations are the entrance and exit doors in pod1 and pod3. Pod1 has two entrances that provide shortcuts to the CICU before reaching the main entrance and are occasionally used by bedside nurses. Pod3 is connected to the step-down unit through an exit door, which is occasionally used by bedside nurse agents in pod 2 and 3 when they want to transfer the patients. The implemented workflow logic in the model for using these attractor locations has taken bedside nurse agents to all pods across all simulation runs, so bedside agents in these pods could encounter all other bedside nurse agents at least once.

5.6 Testing the Study Hypothesis: Comparing Observational Data with Simulation Outputs

This study hypothesizes that the simulation modeling will perform alike empirical testing in evaluating the layout for the likelihoods of creating encounters among care providers in the CICU. To test this assumption, bedside nurses' unplanned interactions (Table 22) from observational data are compared with bedside nurse agents' encounters from simulation outputs (Table 29 & Table 30) in pod1, pod2, and pod3 of the CICU.

The analysis of the observational data showed that bedside nurses in pod2 had a significantly higher number of unplanned interactions with other nurses and care providers compared to those located in pod1 and pod3. Bedside nurses had a 95% chance that the log number of their unplanned interactions increases by 0.05 to 0.32 if they were assigned to rooms in pod2. The outputs of the simulation also showed that bedside nurse agents in pod2 had significantly higher number of encounters with other nurses and care providers compared to those located in pod1 and pod3. Bedside nurse agents had a 95% chance that the log number of their encounters increases by 0.34 to 0.35 if they were assigned to rooms in pod2.

The similar trend in the occurrence of unplanned interactions from observational data and the occurrence of encounters from simulation outputs in relation to bedside nurse locations confirms the assumptions of this study. The simulation model generates similar results to what was found from observational data. Existing studies show that care provider encounters are associated with unplanned interactions. By using simulation modeling, we can predict the impacts of a layout on the occurrence of interactions among care providers by measuring the care provider agents' encounters.

5.7 Impact of Layout on Encounter Episodes

As mentioned in the first chapter (**Error! Reference source not found.**), two l ayout attributes of "compactness" and "betweenness" were selected to explore the impact of design on encounter occurrences, as an example of spatiotemporal events. The analysis of observation data showed that bedside nurses in areas with higher levels of compactness and betweenness in pod2 had higher levels of unplanned interactions (Figure 38, Table 22).

Considering this association, understanding the correlations between layout attributes and proposed spatiotemporal measures can be useful in evaluating layout designs for optimizing such measures. In this section, the outputs of the simulation model are analyzed to understand if betweenness and compactness metrics are associated with encounter measures of CCEt and CCEn.

For each bedside nurse agent assigned location, compactness can be defined by the number of patient rooms within 50 feet radius or the number of neighbor rooms (Table 31). Figure 45 shows a bivariate analysis of number of neighbor rooms for each bedside nurse agent's base location (NN) and the number of bedside agents with whom they had CCEt equal or longer than 10 minutes (numCCEt10). The relationship between the two variables can be defined by:

$$numCCEt10 = 1.1*NN – 2.73$$

Based on this bivariate analysis, maximizing the NN for each decentralized nurse station is associated with an increased number of long encounter episodes with more neighbor bedside nurses. Increased number of encounter episode with long CCEt can be associated with higher rates of unplanned interactions.

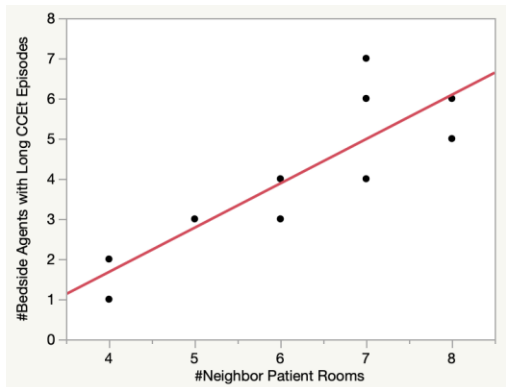


Figure 45 – Bivariate analysis of NN and numCCEt10 for bedside nurse agents (p=0.0008; Rsquare=0.66)

Table 31 – Layout and encounter measures for each bedside nurse agent

	Room	Pod	#Neighbor Patient Rooms	#Adjacent shortest Paths	#Bedside Agents with Long CCEt Episodes	# Mean CCEn
BSN1	2109	2	8	354	5	85.83
BSN2	2110	2	8	354	5	101.57
BSN3	2104-2105	1	7	226	4	89.67
BSN4	2101-2102	1	4	48	2	55.21
BSN5	2103	1	5	180	4	100.71
BSN6	2107-2108	1	8	324	6	119.79
BSN7	2112-2113	2	7	382	6	135.86
BSN8	2115-2117	2	7	136	7	125.83
BSN9	2114-2216	2	7	136	7	95.04
BSN11	2119-2120	3	5	208	3	56.60
BSN12	2122-2123	3	6	178	3	53.76
BSN13	2124-2125	3	6	94	3	33.29
BSN14	2126-2127	3	4	48	1	42.80

We can also explore the impact of “betweenness” as another design variable on encounter episodes. Betweenness can be quantified by the number of times a bedside nurse agent location is on the shortest paths between every two locations. The higher the number of paths, the higher is the betweenness. A bivariate analysis of the number of shortest paths crossing the based location of each bedside nurse agent to all locations and mean CCEn for all care provider agents shows a relationship between the number of shortest paths and mean CCEn values. The higher the number of paths values (higher betweenness), the higher the mean CCEn (Figure 47). This relationship can be defined by:

Mean CCEn = 36.88 + 0.20* (# Shortest Paths)

Based on this bivariate analysis, we can assume that maximizing the betweenness of each bedside nurse agent’s location within the unit can be associated with higher numbers of encounters for each bedside nurse agent to all other care providers and hypothetically more unplanned interactions.

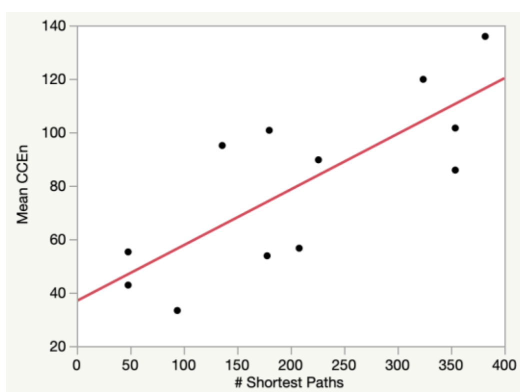


Figure 46 - Bivariate analysis of number of shortest paths and mean CCEn for bedside nurse agents (p=0.003; Rsquare=0.6)

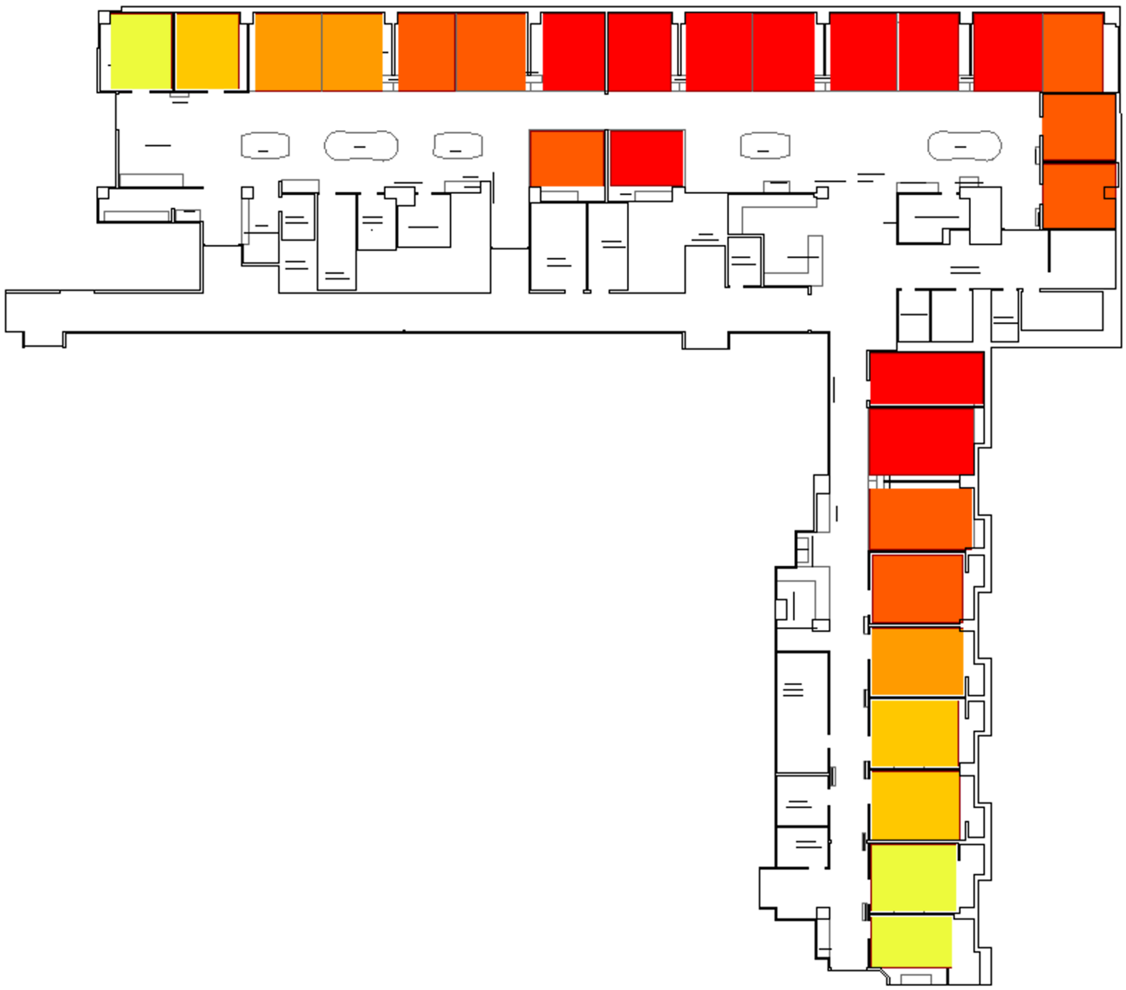


Figure 47 – Betweenness Heat Map (Red: Higher betweenness; Yellow: Lower betweenness)

As an alternative explanation, the impact of walking distance on CCEt and CCEn measures was also explored. It could be hypothesized than agents who walked more were more likely to bump to other agents and have higher encounter measures. Table 32 shows walking distances for each individual bedside nurse agents. A comparison of walking distance between bedside nurse agents did not show any differences between walking distances for agents located in different pods. This similarity can be explained by the allocation of key areas such as medication stations and clean utility rooms in a central location in each pod. The analysis of data did not show any variations in agents' CCEn, and CCEt measures by distance traveled during the working shift.

Table 32 – Bedside nurse agents' walking distances

	Assigned Rooms	Min	Max	Mean	St Dev
Bedside Nurse 1	2109	958.38	1967.54	1438.2	208.34
Bedside Nurse 2	2110	1377.62	2419.73	1857.97	171.03
Bedside Nurse 3	2104-2105	2166.35	8981.46	2787.23	1280.024
Bedside Nurse 4	2101-2102	1679.85	6371.13	2453.13	542.41
Bedside Nurse 5	2103	2127.33	13119.14	4321.31	3116.44
Bedside Nurse 6	2107-2108	739.95	9965.99	3105.62	808.16
Bedside Nurse 7	2112-2113	1564.99	2546.59	2039.94	174.91
Bedside Nurse 8	2115-2117	2629.83	3654.68	3061.16	204.67
Bedside Nurse 9	2116-2114	2137.95	3356.13	2707.08	259.49
Bedside Nurse 11	2119-2120	2662.37	3754	3187.05	248.07
Bedside Nurse 12	2122-2123	2035.09	2980.38	2427.06	201.2
Bedside Nurse 13	2124-2125	1903.56	2879.77	2274.76	192.59
Bedside Nurse 14	2126-2127	3015.04	5026.36	3960.25	434.25

CHAPTER 6. DISCUSSIONS

6.1 Conclusions

The focus of this research was to develop a simulation model for measuring the spatiotemporal experience of building occupants in relation to design attributes of a layout. This study uses a pediatric cardiac intensive care unit as the study site in order to investigate impacts of layout on care providers' face-to-face encounters as an example of spatiotemporal events. The supporting data for building the simulation model was collected on the study site through observational methods and shadowing. This information helped answer the first question of the current study about understanding how care providers spend their time in different activities and locations within the unit.

The analysis of the care providers' time and activity data informed modeling strategies for building the simulation model, including agents profiling, states, workflow, and activities. In order to simulate care provider agents' behaviors, different categories of activities, including structured and unstructured activities, as well as their locations and time distributions, were identified and implemented into the simulation model. The simulation model in this study uses a multi-method approach by incorporating both agent-based and discrete event simulation modeling techniques.

The second question of this study was how to model the ongoing structured and unstructured activities of individual care providers to simulate the system. To answer this question, a combination of event-based activities, scheduled processes, and Markov Chains probabilistic rules are used to define the agents' movement logics and transitions in the model. The Markov Chains process modeling in this study included custom programming for using estimations from stochastic matrices to determine agents' states, based on probabilities of transitions between activities and locations.

The third question of this study was about understanding which aspects of current simulation techniques need to be further developed for measuring spatiotemporal events. The Anylogic simulation platform used for this study did not include spatial analysis methods but presented a customizable platform where the required methods could be developed and added to the simulation model. Spatial analytics methods were integrated into the simulation platform in order to evaluate spatial relationships between agents such as co-presence within defined distance thresholds, field of view, and line of sight assessments and measure their spatiotemporal experience. Using custom programming, the simulation model evaluates and records care providers' encounters at defined time steps.

The main outputs of the simulation model in this study are a record of care providers' encounter episodes, including care provider-to-care provider encounter times (CCEt) and care provider-to-care provider encounter counts (CCEn). The encounter measures were recorded for all individual care provider agents across multiple simulation runs to capture stochasticity of output data.

The encounter outputs of the simulation model showed how spatiotemporal experience of agent varied based on their locations. Bedside nurse agents in pod2 had significantly longer mean total durations of encounters (CCEt) with all bedside nurses and other care providers, compared to bedside nurse agents in pod1 and pod3. They also had longer durations of encounter (more than 10 minutes) to significantly more bedside nurse agents (CCE10) compared to those in pod1 and pod3. Bedside nurse agents in pod2 had significantly higher mean total encounter numbers (CCEn) to all other bedside nurse and care providers, compared to those located in pod1 and pod3.

This study used two quantified measures for layout compactness and betweenness to understand how changes in these layout attributes were associated with changes in encounter episodes for bedside agents located at different locations. Bivariate analyses of simulation encounter output data, and these layout measures showed that increases in number of neighbor rooms were associated with increases in the number of encountered bedside nurse agents with longer encounter durations (CCEt10) for each bedside nurse agents. It also showed that increases in the number of adjacent walking paths were associated with increases in mean total encounter numbers per other care providers (CCEn).

The final question of the current study was whether simulation modeling help in understanding the impacts of design on care providers' spatiotemporal experience. This study hypothesized that the simulation modeling will perform alike empirical testing in evaluating the layout for the likelihoods of creating encounters among care providers in the CICU. The analysis of the observational data showed that bedside nurses in pod2 had a significantly higher number of unplanned interactions with other nurses and care providers compared to those located in pod1 and pod3. The outputs of the simulation also showed that bedside nurse agents in pod2 had significantly higher number of encounters with other nurses and care providers compared to those located in pod1 and pod3.

The similar trend in the occurrence of unplanned interactions from observational data and the occurrence of encounters from simulation outputs in relation to bedside nurse locations confirmed the assumptions of this study. Based on this similarity, we can assume that by measuring the layout impacts on occurrence of encounters, we can understand the impact of layout on the likelihood of unplanned interactions among care providers in designing healthcare environments. By enhancing simulation platforms through the integration of spatial analysis methods, we can further understand impacts of design on building occupants' spatiotemporal experience at initial stages of design.

A broad range of research studies, including those in the evidence-based design field and architectural morphology, have reported how spatial analysis metrics are associated with care provider outcomes in healthcare settings. By identifying these metrics and integrating them in simulation platforms through technological methods developed in this study, we can better understand the impact of layout on care providers' spatial experience, considering the stochasticity of space occupancy patterns.

The simulation model developed in this study can help further understand the impacts of alternative design options on care providers encounters in the CICU. The agents' locations in the simulation model are assigned through parametrized locations (as opposed to absolute locations). To test an alternative design option with the developed model, it is possible to quickly change the location parameter of agents and run the simulation model with the defined care processes and workflows.

We can further validate the findings of this study by collecting data from other intensive care environments. This study collected nurses' activity data only from one setting. By collecting more data from other settings, we can explore how the simulation model can be further improved to be used as a generalizable tool. The recent developments in data collection technologies allows for collecting data in larger scales from similar settings. By accessing to larger data sets from other intensive care units, we can identify the workflows that are similar in all intensive care units, as well as the workflows that are specific to each unique setting.

6.2 Future Research Directions

6.2.1 Experimentation

As a next step for this research project, the simulation model can be used to test the impact of alternative design options on creating encounter episodes. Experimentation in the simulation model can be done through changing different model parameters and logic. Since the focus of the current research project is to study the layout design, the experimentations of the study can involve changing the attributes of the layout. Interventions can be as general as changing the overall layout and comparing encounter levels for each provider with those of the initial layout. Interventions can also be more specific such as changing the location of agents on the layout, their, changing their movement routing strategies, or changing the layout attributes such as removing physical barriers. Since agents' locations in the simulation model are not absolute and assigned through parametrized locations, it is possible to easily change the layout for experimentation.

The experimentation can also be done with changing the parameters defining encounters, including distance threshold and the field of view degree. Any of these changes may or may not create significant changes in the encounter levels, which can be subject to further research and investigation. By letting agents to simulate their movements and occupy the space, and by recording agents' logs on encounter episodes, we can compare the performance of different design options for agent encounters.

Another opportunity with the developed simulation model is to measure care providers' encounter episodes during different activities independently. Several studies have shown that minimizing nurses' distractions on medications paths are associated with fewer errors and reduced walking distances (Seo et al., 2011). We can measure the care provider encounter episodes on medication delivery paths and examine if specific bedside agents' locations had fewer CCEn on medication delivery routes. The simulation model can be used to evaluate multiple design alternatives and prioritize options with minimized encounter rates on medication delivery routes and maximized encounter rates in other locations.

An alternative experimentation approach can involve the integration of multiple spatiotemporal measures into the simulation model. Through a multi-objective experimentation framework, we can simultaneously evaluate the performance of a given layout against multiple spatiotemporal events. The set of spatiotemporal measures can include care provider-to-care provider encounters, in addition to care provider to patient encounters, care provider walking distances, care providers' dynamic social densities, dynamic team formation episodes , care providers or patients' duration of exposure to natural light and outside views, care providers or patients exposure frequency to peak noise levels, or any other spatial metrics which involves time-related dimension.

6.2.2 Application in Other Settings

The study focused on exploring care providers' spatiotemporal experience based on the layout design and occupancy patterns in a healthcare setting. Although the study site selected for this study was a pediatric cardiac ICU, the simulation model can be used to study care providers' spatiotemporal experience in other healthcare settings such as inpatient units and outpatient clinics through adjusting the agents' state transition logic.

The proposed methods and techniques in this simulation study can also be modified to apply in similar studies in other settings such as airports, workplaces, retails, and educational buildings. They can be used for analysis of spatiotemporal experience of passengers in airport terminals where visual exposure and proximity to wayfinding elements and gates can be determining in passengers' travel experience. In workplace environments, such methodologies can be implemented to study design opportunities for improving teamwork and collaborations by increasing unplanned encounters among team members in common and shared workspaces. In retail environments, we can apply similar methodologies for evaluating merchandise spatial allocations in order to enhance marketing opportunities and customer's' shopping experience through maximizing visual exposure and facilitating access to specific items. In educational settings such as universities and schools, similar methodologies can be applied to study design options than can boost learning opportunities by increasing their exposure time to natural light, learning materials, and classmate teamwork activities.

6.2.3 *Developing Spatial Analytics Packages for Simulation Platforms*

Development of spatial analysis methodologies, such as those developed in this study, can initiate a discussion about the necessity of advancing current simulation packages by embedding spatial analytics to agents' behavior. The workflow and techniques suggested by this dissertation can be expanded and further developed in creating add-ons for simulation platforms and visual programming interfaces or in creating stand-alone simulation platforms for spatial analytics.

Currently, the spatial analytic methods used in this study are defined through a custom java class with one method, which evaluates the encounter episode between selected agents and other defined target agents. The current method can be further optimized to increase the computational efficiency of calculations and improved for visualization purposes. Additional spatial analytics methods can be defined and added to this class for evaluating other aspects of agents' spatiotemporal experience mentioned in section 5.3.1. The custom Java class developed in this study can be incorporated into Anylogic software and become available to other researchers and users.

6.2.4 *Application of Indoor Location Tracking Systems*

The current study used manual on-site data collection using custom GIS Collector features to collect data on care provider activities during 300 hours of observation. Although this method allows researchers to procure valuable information on care provider activities and space occupancy, which are not accessible through other data collection means, it has a few limitations limitation. First, it requires a significant number of human-dedicated hours for observation and data collection on the site to be able to collect enough data to draw any statistically reliable conclusion. Second, it involves bias and errors incorporated in all manual data collection methods. Third, the presence of researchers on the site might affect the care providers' activity patterns based on perception "being watched by someone", even if the observation procedure does not interfere with the subject under the study. For these reasons, alternative automated data collection methods can be more beneficial for higher levels of accuracy, efficiency, and reliability.

A variety of indoor positioning systems have been developed and used in similar studies to track and record the spatial coordinates of individuals at defined time intervals. Active Radio Frequency Identification (RFID) devices were used to assess mutual proximity and dynamics of person-to-person interactions using OpenBeacon Proximity Tags (Cattuto et al., 2010; Isella et al., 2011; Stehlé et al., 2011). Short-range lightweight wearable RFID tags were used to detect face-to-face interactions to study the impacts of a new building on social behaviors in a research institution. (Brown et al., 2014). Wineman used a UWB location system and wearable tags to map patterns of spatial use and real-time social interactions (Wineman et al., 2014). MIT sociometric sensors were used in a recent study to record communications between care providers in hospital wards. Care providers wore badges that contained Bluetooth and infrared sensors and recorded information about the duration and frequency of communications (Pachilova et al., 2017).

The current application of such technologies in similar studies and the advancement of indoor location tracking systems allows researchers to access a broader pool of data with higher precision in order to improve the accuracy of research findings.

6.2.4.1 Application of a UWB System in the Current Study

The current study initially planned to include a second data collection phase using Ultra Wide Band (UWB) technology to collect more data on care providers' movements and activities, including walking speed on different activities, path deviations, and occupancy distributions. For this purpose, a research collaboration with an industry partner was established to provide the location tracking system required for the study. To evaluate the UWB system, a test environment was set up at Georgia Tech's SimTigrate Design Lab as a "proof of concept" test to evaluate and optimize the performance of the system and data accuracy for the purpose of the study.

In the next step, a research protocol was developed for using the UWB system in the CICU for collecting data. The study protocol was submitted to both the Georgia Institute of Technology and Children's Healthcare of Atlanta institutional review boards and was approved. In the next step, the engineering, information technology, and infrastructure departments of the hospital reviewed the UWB system for possible risks and interference with the current system and confirmed that the proposed system was safe to install in the CICU. The study protocol submission and approvals are attached in APPENDIX A.

To this time, the proposed data collection phase is still awaiting the official contract with the hospital and founding resource. Therefore, it is not included in the current study. In the next section, the proof of concept study in the test setting is explained, which includes a description of the refinement process and selected technical settings for actual hospital implementation.

6.2.4.2 Testing an Indoor Location Tracking System: Repp Health Eo System

The In order to examine the feasibility of using a UWB system for the proposed study phase and identify settings required for the test in hospital, a proof of concept test setting was set up in the lab environment using Repp Health Eo System. The test setting included 5 IoT gateways (anchors) and 4 Ultra -Wide Band (UWB) tags. The anchors were installed on the ceiling so that every tag had a clear line of sight to two other anchors. The first anchor was connected to the Ethernet rout, and all the anchors were daisy-chained together (Figure 48).

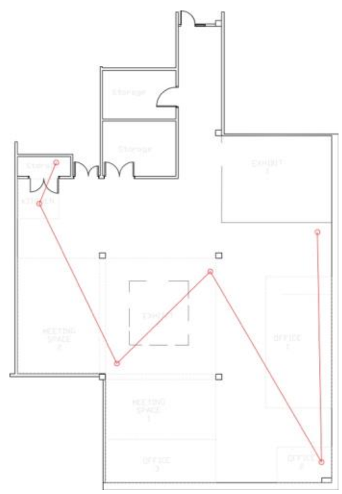
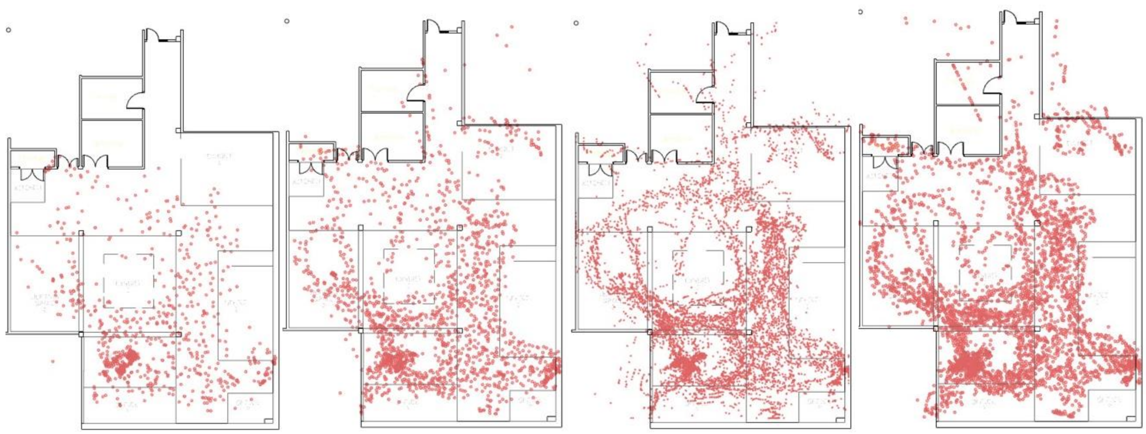


Figure 48- Location of ceiling anchors in the test setting

The functionality of tags was tested through the interactive interface. Each tag was set up on a different rate (1HZ, 2HZ, 5HZ, 10 HZ) and was carried around by the researcher to collect sample data. The collected data was then mapped on the layout to compare the results for different update rates. Collected data included x and y coordinates of recorded relocations, which was used to visualize points representing them on the layout.

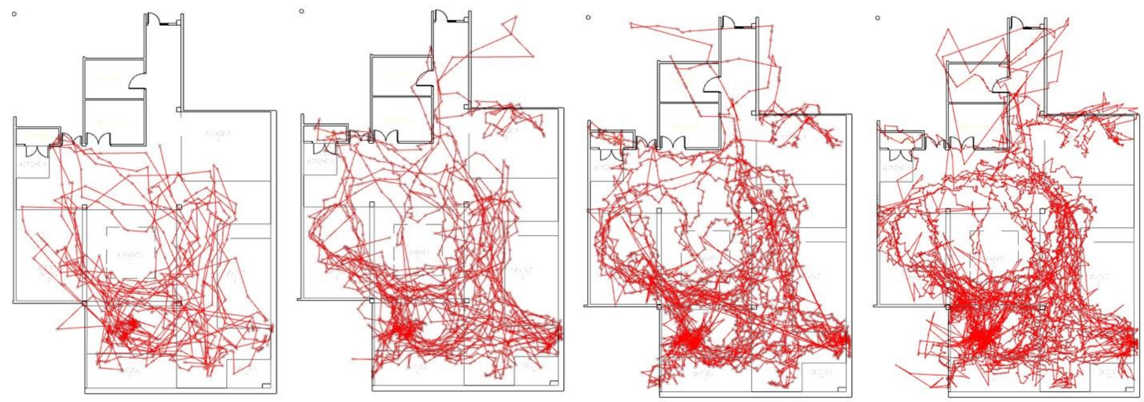
Table 33 – Sample data recorded for a tag

x	y	device_event_time (Unix Epoch Time)
19112	26165	1556463636.06959
19113	26156	1556463698.62811
19099	26163	1556463760.05658
19091	26168	1556463822.6971
19090	26149	1556463884.16171
19089	26151	1556463945.59222
19090	26150	1556464005.72111
19095	26157	1556464067.97744



Tag 1 (1HZ) Tag2 (2HZ) Tag3 (5HZ) Tag 4 (10HZ)

Figure 49 – Collected data points mapped on the layout



Tag 1 (1HZ) *Tag2 (2HZ)* *Tag3 (5HZ)* *Tag 4 (10HZ)*

Figure 50 –Movement paths mapped on layout

The points were consecutively connected to show movement paths of the person carrying the tag. After a comparison of 4 frequencies, the 10 HZ update frequency was selected as it presented higher accuracy and consistency in capturing the movement paths.

As data was mapped on the layout, a few issues appeared: the jiggling data points recorded when tags remained in the same location, the incorrect data points recorded when tags left the area, the jumping data points where tags were moving. In the first step, the smoothing factor on the caching server was updated to 3, meaning that the location for three consecutive data points was averaged. This modification intended to nullify much of the erroneous locations. The untrustworthy data, including outliers on a path, were removed as well.

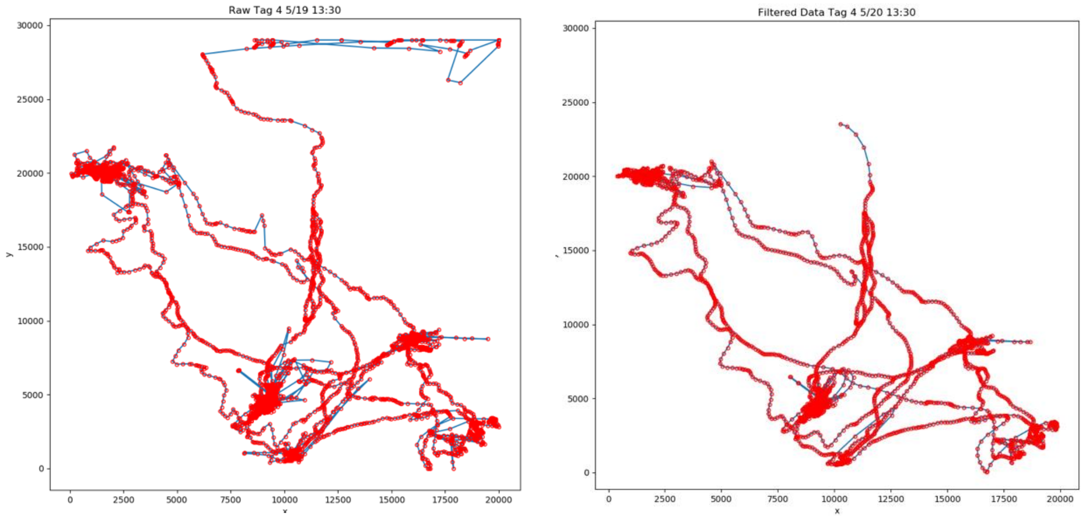


Figure 51- Movement points before and after applying the smoothing algorithm

Figure 51 shows the impact of applying the smoothing algorithm on the raw data. Many of the areas that have bad data sticking out from the raw have been removed. Two serial tasks consisted the process of filtering data at this stage. First, a combination of anchor count (number of receiver anchors that reported the location at that point) and quality metric (quality of received signals from tags by the receivers) to triage bad data (anchor_count^2 * quality > 50,000). On the remaining, a rolling window was used to calculate a triangular moving average using 5 data points. Although this algorithm was able to remove unreliable data to some extent, some outliers still existed, which required statistical identification and exclusion of these data points.

The next step was to apply an optimized weighted average filter. Figure 52 shows an example of applying the filter on a sample of raw data (78 seconds). As can be seen in the picture on the left, there are some areas where data appears jagged, and some data points are assumed to be erroneous compared to normal human motion. The picture on the right shows the raw data after being processed through an optimized weighted average filter. As can be seen, a significant improvement over the raw data is observed. The erroneous data points are excluded more effectively from the positional data, and the sparsity in certain areas is improved. The updated algorithm used knowledge about how each data point was calculated and how well the tag could communicate with each location gateway to triage data.

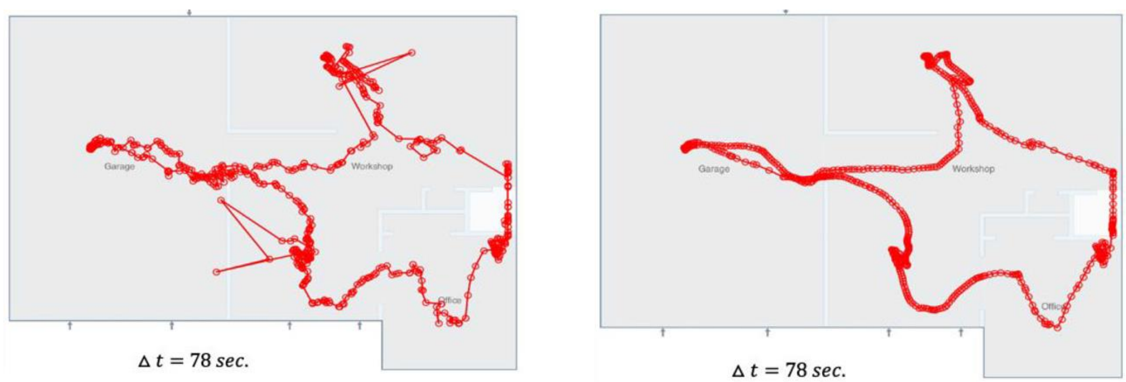


Figure 52-Filtered data before and after applying the optimized weighted average filter

To test the weighted average filter on a bigger data sample, 2 hours of tracking data in the test setting were examined. Figure 53 presents the collected data points in the lab setting during the 2-hour test in the lab setting (the rectangle shows the boundaries of the test setting). As expected, the central tracking areas have better communicating with the receiver anchors. The extreme areas on the edges show poor communication with anchors. Regarding the signal quality, a significant number of data points present a low signal quality, despite the high communication levels with anchors. The signal qualities about 8000 provide good accuracy for tracking. The most common sources of bad signal quality are bodily occlusion and low anchor density. Considering that the test setting and location of tags on the body did not cause major body occlusion, the anchor density was probably the source of low signal quality.

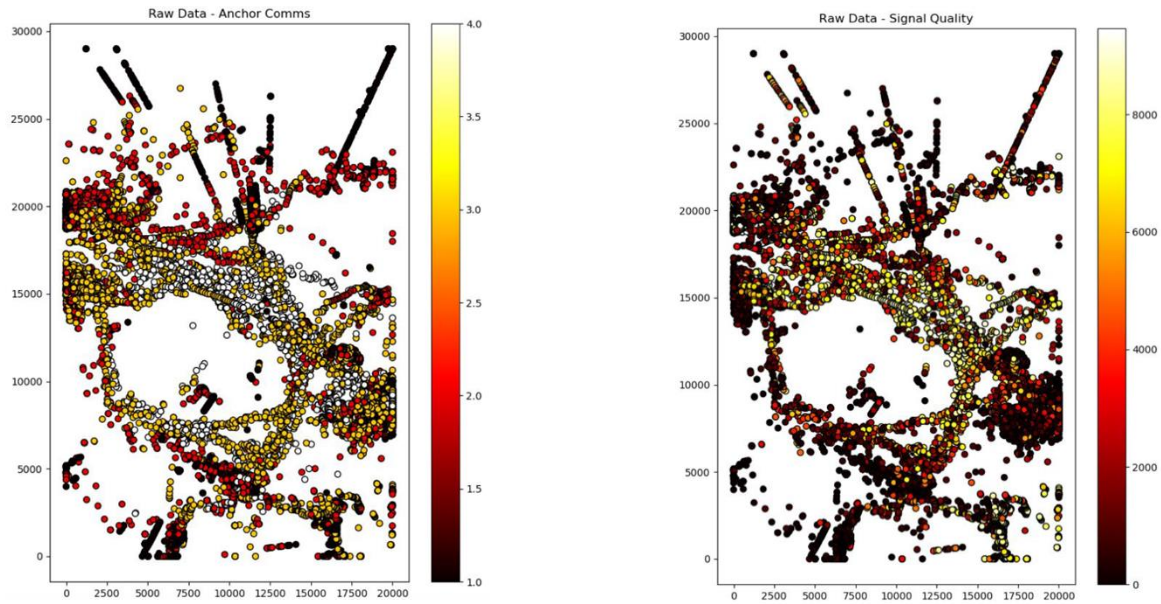


Figure 53- Anchor communications and signal quality for the recorded data

As for the impact of the filter on smoothing the raw data, the 2-hour test also confirmed the effectiveness of the weighted average filter. The travel paths are significantly smoothened while maintaining the accuracy of data, and extreme deviations from the path are removed (Figure 54).

The results of the proof of the concept test shows promises in feasibility of implementing Repp Health Eo UWB system in the hospital test setting by increasing anchor density.

Figure 54- Comparing filtered (blue) and unfiltered (green) data points on 3 different travel paths

6.3 Contributions

This study contributes to the field by helping design researchers understand impacts of layout design on spatiotemporal experience measures of building occupants during design phases through simulation modeling. It adds a new dimension to current simulation modeling studies for the design and planning of the healthcare facilities by integrating spatial analysis metrics into current simulation platforms for simulating agent's workflow and activities. The proposed model can be applied in measuring the spatial experiences of agents in order to humanize simulation models further and move towards evaluating buildings' performance based on user experiences. Findings of this research project will be beneficial in advancing spatiotemporal and behavioral studies on care provider and patient outcomes in healthcare and non-healthcare settings.

By creating a simulation model as a virtual laboratory, we can rapidly test different layouts and design parameters at conceptual design phases instead of waiting for the buildings to be designed, built, and occupied and later be studied through post-occupancy evaluations. Simulation modeling allows designers to explore the impact of design features on spatial experience in a controlled environment and understand the causality of relationships between design variables and spatial experience measures.

The contributions of this study can be divided into knowledge-based and methodological categories. In the knowledge-based category, this study provides a breakdown of care provider activities in an intensive care unit by describing care providers activities in relation to space occupancy patterns. Through analysis of observational data, this study offers a unique understanding of space utilization in intensive care units, which helps understand how and why care providers move between different locations to perform their daily tasks.

Another knowledge-based contribution of this study is providing an understanding of care providers interactions. This study helps understand the mechanism of interactions in intensive care units, reasons of interactions, different types of interactions, including planned and unplanned categories, and spatial qualities of locations where interactions happen. This information can be used to understand how the design of intensive care units can facilitate or limit the occurrence of each type of interactions.

This study also contributes to the body of knowledge in the field by investigating impacts of layout design on care providers' spatiotemporal experience. By analysis of simulation data in relation to bedside nurses, it explains how layout attributes of intensive care units such as compactness and betweenness can be associated with care provider-to-care provider encounter measures including duration and frequency of encounter. By understanding care provider encounters in relation to their location within the unit, we can have a better approximation for the likelihood of unplanned interactions among them.

In the methodological category, this study enhances exiting technologies in order to make them useful to design researchers who are interested in understanding the building occupants' movement patterns and the impact of layouts on occupants' experience. First, it develops a workflow for customizing the GIS Collector application to be used for indoor data collection purposes. On-site data collection in healthcare environments is a challenging and fast-paced task which requires recording a considerable amount of data on activities and locations of multiple groups of care providers. Mapping the collected data on site maps also can be a time-consuming process. Using the workflow developed in this study, the observational on-site data collection can be more accurate and efficient.

The main methodological contribution of this study is the integration of spatial analytics methods in the simulation platforms in order to evaluate and measure agents' spatiotemporal experience. This method allows for real-time analysis of care-providers' encounter measures while simulating their workflow and processes and generates outputs of recorded measures for further analysis and research. Contrary to similar methods which have limitations in terms of modeling agents' underlying process models and state transition logic or spatial analytics, this method presents a comprehensive approach by combining the two aspects through further development of existing methods in a powerful simulation platform.

APPENDIX A. RESSEARCH PROTOCALS

A.1 Georgia Tech IRB Approval

Georgia Tech
Office of Research Integrity Assurance

Protocol Number: H18388
Funding Agency: N/A
Review Type: Not Human Subjects/Not Research Determination
Title: Activity Patterns of caregivers in ICU

October 17, 2018
Craig Zimring
ARCH
craig.zimring@design.gatech.edu

Dear Dr. Zimring:

The Institutional Review Board (IRB) has carefully considered your proposal referenced above. Based on the materials provided, we have determined that it does not require IRB review because it does not meet the definition of research with "human subjects" as set forth in Georgia Tech policies and procedures and federal guidelines. This determination was made because no information is being collected about the individuals who are being observed in this study.

Please note that this determination does not mean that you cannot publish the results. If you have questions about this issue, please contact me.

This determination could be affected by substantive changes in the study design, subject populations, or identifiability of data. If the project changes in any substantive way, please contact our office for clarification.

If you have any questions concerning this determination or regulations governing human subject activities, please feel free to contact me at 404.385.5208.

Thank you for consulting the IRB.

Sincerely,

Scott Katz, MS, CIP
Research Associate
Compliance and Regulatory Affairs
Office of Research Integrity Assurance
Georgia Institute of Technology

A.2 Children's Healthcare of Atlanta IRB Approval

Children's℠
Healthcare of Atlanta

Date: 01/02/2019

NOTIFICATION THAT STUDY IS EXEMPT FROM FURTHER IRB REVIEW

Project Title: Activity Patterns of Caregivers in the Pediatric Cardiac ICU
Principal Investigator: Nikhil Chanani, MD
CHOA IRB#: 18-194
Determination Date: 01/02/2019
Study Site:
- ☒ Children's at Egleston
- ☐ Children's at Scottish Rite
- ☐ Children's at Hughes Spalding
- ☐ [Insert Private Practice Name]

Dear Dr. Chanani:

Thank you for your submission to the Children's Institutional Review Board (Children's IRB). Upon review of the study materials, Children's IRB determined that the proposed protocol activities are exempt from further Children's IRB review per the Federal human subject protection regulations (45 CFR 46). Specifically this study falls under category (b)(2).

Additionally, Children's IRB serves as the Privacy Committee for Children's Healthcare of Atlanta, the covered entity for the study activities as defined in the Health Insurance Portability and Accountability Act of 1996 (HIPAA). Children's IRB determined that protected health information will not be accessed and not recorded in the course of this study.

You are now authorized to commence your study with no requirements for continuing review or approval by Children's IRB based on the current protocol. If, in the future, the study plans change in a way that affects the exemption status, a request for modification must be submitted for Children's IRB review and approval before the changes are implemented.

Thank you very much for your respect of the mission of the Children's IRB to protect human research subjects participating in studies involving Children's Healthcare of Atlanta.

Sincerely,

Anna Lum
IRB Coordinator

REFERENCES

REFERENCES

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